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COMPUTER PROGRAMS FOR SCORING TEST DATA WITH ITEM CHARACTERISTIC CURVE MODEL

Isaac I. Bejar
and
David J. Weiss

RESEARCH REPORT 7
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PSYCHOMETRIC METHODS PROG
DEPARTMENT OF PSYCHOL
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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Three computer programs are described for scoring test response data using item characteristic curve (ICC) or latent trait models. The rationale and mathematical basis of both maximum likelihood and Bayesian ICC scoring methods are presented, as well as some data comparing the two methods of scoring. The three computer programs are designed for scoring conventional (linear) test data (LINDSCO) in dichotomous response format, adaptive test dichotomous data (ADADSCO), and conventional (linear) test data scored by polychotomous ICC models (LINPSCO). Options available in these three general

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purpose programs are described, and examples of the input and output are given for each program. Complete FORTRAN listings of the three programs are included.

LEVEL II

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Appendices

Acknowledgments

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Disclaimer

While every attempt has been made to insure the accuracy of the computer programs described in this report, the authors assume no responsibility for the accuracy or performance of the programs.

Technical Editor: Barbara Leslie Camm

Computer Programs for Scoring Test Data with Item Characteristic Curve Models

Although latent trait test theory, or item characteristic curve (ICC) theory, has been developing since Lawley's (1943) paper more than 30 years ago, applications of the theory have appeared only recently. However, there are indications that latent trait test theory is beginning to reach the practitioner who is concerned with test development and usage in applied settings. This is evidenced,not only by the increasing number of journal articles concerned with latent trait test theory (e.g., the summer 1977 special issue of the Journal of Educational Measurement on applications of latent trait models) and in presentations and training sessions at professional meetings, but also by its application in adaptive (Weiss, 1976) or tailored (Lord, 1970) testing.

A potential disadvantage of latent trait test theory is that its use often involves complex computational procedures. To apply ICC models to the development of tests and their scoring, the psychometrician must be able to estimate the ICC parameters of the items in the test,and then use them in conjunction with the response data of a new group of testees in order to estimate their trait scores (e.g., ability or achievement levels). A number of computer programs are available for estimating ICC item parameters (these are summarized in Appendix Table A). However, there appeared to be no general programs available for scoring test data with ICC models when item parameter estimates were available from previous data sets. This report describes several programs designed to meet this need.

An Introduction to Test Scoring

The problem of test scoring can be conceptualized as the process of summarizing a testee's answers to a set of test questions into a single number in such a way that the score will be indicative of the testee's position on the trait being measured by the test. The most common test scoring strategy is to add the number of correct answers and to transform the score into some type of standard score or percentile to add interpretability. Historically, the number-correct score has been used because it is easy to calculate, and in pre-computer days this was an essential requirement of a test scoring procedure. As a general procedure for scoring tests of ability and achievement, however, the number-correct score has several deficiencies.

Inadequacies of the Number-Correct Score

One major problem with the number-correct score is that it is possible for the same number-correct score to be obtained in several different ways; that is, several response patterns can result in the same number-correct score. If the items in a test are all of equal difficulty and discrimination, and therefore are essentially replicates of each other, this will have little effect on the number-correct score, since different response patterns among

replicate items are of little consequence. But it is a very rare test--and one which would have little general measurement utility--which would have items that are all replicates of each other with regard to difficulty and discrimination.

When test items differ with respect to difficulty or discrimination, they are no longer replicates. Under these circumstances, different patterns of response to the same set of items convey different information with regard to a testee's trait level. The testee who correctly answers only five very difficult items in a test is likely of higher ability than the testee who correctly answers only five very easy items in the same test. Although the total number-correct score is the same for these two testees, their trait level estimates derived from latent trait or ICC theory will differ. An additional unattractive feature of the number-correct score is the fact that the number of possible scores is determined by the number of items in the test. Thus, if a test consists of only 10 items, only 10 unique scores are possible. Although this may be sufficient in some applications, in others it might be desirable to obtain a finer gradation of scores.

The inadequacy of the number-correct score as a general test-scoring procedure is most obvious when considering how to score responses of testees who have been administered different sets of items, as in adaptive or tailored testing. In these kinds of tests, number-correct scores are completely inappropriate, since different testees will receive items of different difficulties and discriminations as well as different numbers of items in an adaptive test. In addition, the proportion of correct responses obtained by all testees will be approximately the same in a well-designed adaptive test (e.g., Weiss, 1975).

ICC-Based Scoring

The scoring programs described in this report use considerably more refined approaches than a mere adding of correct answers and are usable for scoring both conventional and adaptive test data. This refinement is possible because ICC theory makes very explicit specifications about the relationship between performance on a test item and the testee's position on the trait, θ. This relationship is referred to as the *item characteristic curve* (ICC; Lord & Novick, 1968) when the items are scored into two categories (correct or incorrect) or, when there are more than two score categories, as the *operating characteristic function* (Samejima, 1969).

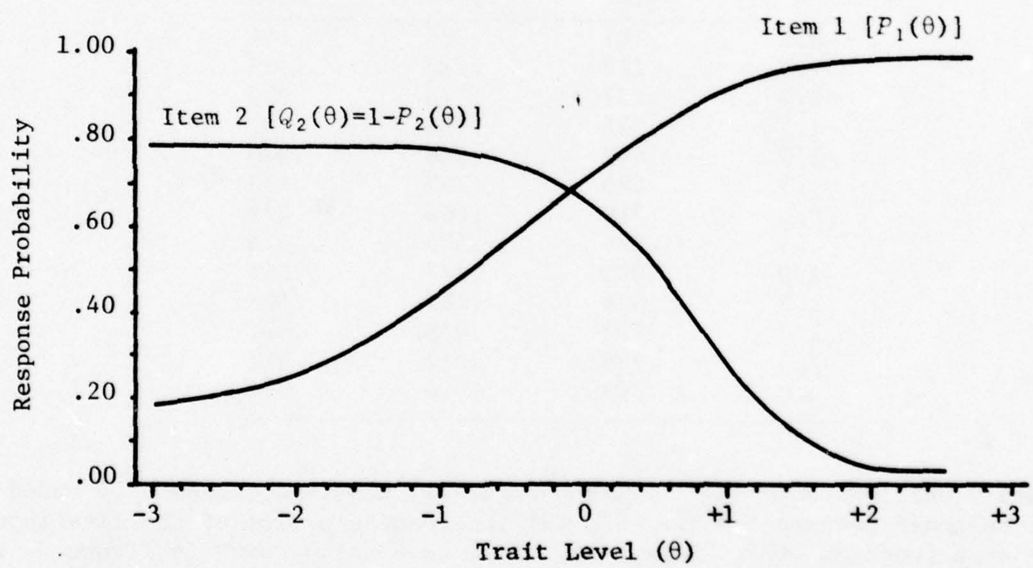
In the context of latent trait test theory, scoring may be conceptualized as finding the value of θ (i.e., the trait being measured) most "compatible," in some sense, with a given pattern of responses to the test items, given the ICC item parameters for each item answered. For maximum likelihood scoring, the score associated with a given response vector is that value of θ for which the likelihood of the response vector is maximum. For Bayesian scoring, the score is usually either the value of θ that minimizes the mean squared difference between the estimated θ and the "true" θ, or the value of θ that is most probable given the observed responses.

Maximum likelihood scoring. The details of the maximum likelihood scoring procedure are presented below. However, a conceptual explanation based on two

dichotomously scored test items will serve to explicate its rationale.

Figure 1 shows response probability curves for two test items--Item 1, which was answered correctly (resulting in an ICC plot of the probability of a correct response), and Item 2, which was answered incorrectly (resulting in a descending plot of the probability of an incorrect response, or 1 minus the ICC). The ICC curves for the two items are described by three parameters: (1) difficulty, b, which is the location of the ICC on the trait (θ) continuum at the point of maximum slope of the ICC (b=-.5 for Item 1 and .75 for Item 2); (2) their discrimination, a, which is proportional to the slope of the ICC at b (a=.8 for Item 1 and 1.4 for Item 2); and (3) "guessing," c, the lower asymptote of the probability of a correct response at $\theta=-\infty$ (c=.16 for Item 1 and 1-.78=.22 for Item 2).

Figure 1
Response Probability Plots for a Correctly Answered Item (Item 1)
and an Incorrectly Answered Item (Item 2)



The first step in maximum likelihood scoring consists of determining the likelihood of the response pattern (correct response to Item 1 and incorrect response to Item 2). Assuming local independence, which means that responses to the test items have nothing in common except their relationship to the underlying trait, θ, the likelihood of a response pattern at any value of θ can be determined by multiplying the separate probabilities of the responses in the response pattern for that value of θ. The value of θ for which the likelihood is maximum is the maximum likelihood estimate of θ.

Conceptually, this can be illustrated with the ICCs in Figure 1 by using discrete values of θ, such as those shown in Table 1. For example, at θ=-1.0, the probability of a correct response to Item 1 (scored as 1) is .442 and the

probability of an incorrect response to Item 2 (scored as 0) is .768; multiplying these values gives the likelihood of the [1,0] response pattern as .340. At θ=+1.0, the probability of a correct response [1] to Item 1 is .903 and the probability of an incorrect response to Item 2 is .277; the likelihood of the [1,0] response pattern is therefore .250. Similarly, at θ=0.0, the probability of a correct response to Item 1 is .718 and the probability of an incorrect response to Item 2 is .668, resulting in a likelihood for the [1,0] response pattern of .479. This process of computing likelihoods for the [1,0] response pattern can be repeated for a large number of values along the θ continuum.

Table 1
Probability of a Correct Response to Item 1 [$P_1(\theta)$] and Probability of an Incorrect Response to Item 2 [$Q_2(\theta)$] for Selected Values of θ (Item 1: a=.8, b=-.5, c=.16; Item 2: a=1.4, b=.75, c=.22), and Values of the Likelihood Function [$L(\theta)$]

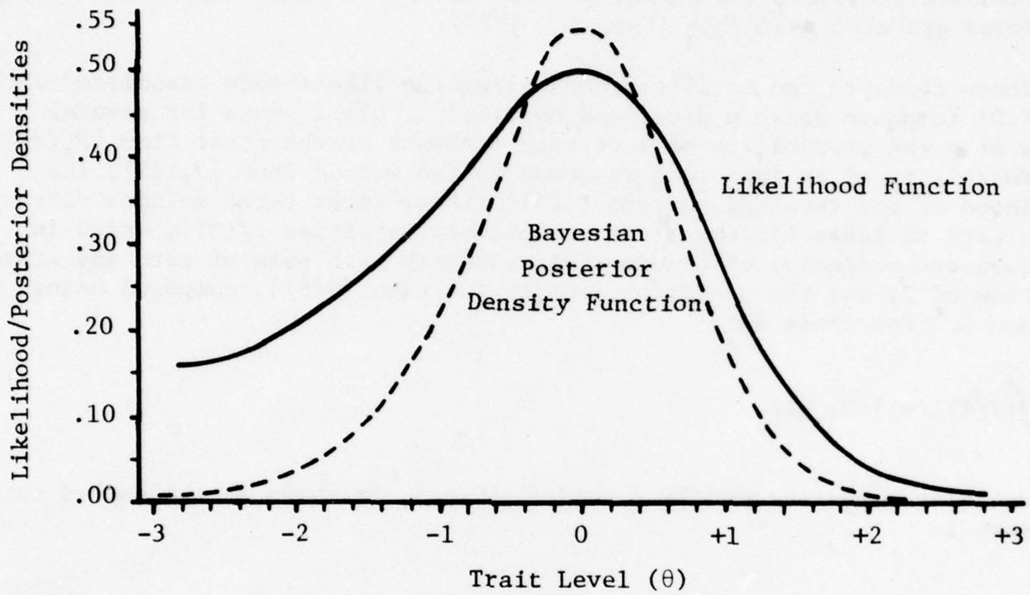
θ	$P_1(\theta)$	$Q_2(\theta)$	$L(\theta)$
-3.0	.187	.780	.146
-2.5	.212	.780	.165
-2.0	.257	.779	.200
-1.5	.332	.776	.257
-1.0	.442	.768	.340
.5	.580	.742	.430
0.0	.718	.668	.479
.5	.828	.503	.416
1.0	.903	.277	.250
1.5	.948	.112	.106
2.0	.973	.038	.037
2.5	.986	.012	.012
3.0	.993	.004	.004

The result of computing likelihoods for all possible values of θ based on the response pattern and the relevant ICCs can be a plot of the likelihood values as a function of θ. This plot, shown as a solid curve in Figure 2, is called a likelihood function. As can be seen, the maximum of the likelihood function in Figure 2 occurs at about θ=0.0 (actually .01). Thus, θ=.01 can be considered the maximum likelihood estimate of θ associated with the [1,0] response pattern, given the parameters of the ICCs for the items generating that response pattern. The maximum likelihood θ estimate is thus the value of θ which maximizes likelihood of the given response pattern for items with the specified ICCs.

The generalization of the scoring method for more than two items is straightforward. For each value of θ, the likelihood would be determined by multiplying the response probabilities for the appropriate ICCs (based on the specified response pattern) across all items that have been answered. Thus, for n items, n probabilities would be multiplied at each value of θ to obtain the likelihoods. The resultant likelihood values for all values of θ

could be plotted; and the maximum of the likelihood function would be used to identify the value of θ that gives the observed response pattern the greatest probability of occurrence.

Figure 2
Likelihood Function and Bayesian Posterior Density Function for the [1,0] Response Pattern



Maximum likelihood scores are intuitively appealing; at the same time, they have a number of optimal statistical characteristics, at least asymptotically (i.e., when large numbers of items are administered). Of special relevance is the fact that as the number of items in the response pattern increases, it can be shown (Kendall & Stuart, 1961) that maximum likelihood estimates have minimum variance; and the reciprocal of that variance is known as the information function of θ. As a consequence, different scores (i.e., θ estimates) can have different degrees of accuracy as estimators of θ (Birnbaum, 1968; Samejima, 1969).

Bayesian scoring. Although the numerical details of maximum likelihood and Bayesian scoring are substantially different, the two methods are conceptually very similar. Bayesian scores are based on the likelihood function modified by the prior probability density function of θ. The prior probability density function describes the assumed distribution of θ in the population of individuals to be tested.

To illustrate, call $L(\theta)$ the likelihood of the response pattern for a given θ value. Now call $f(\theta)$ the prior probability density associated with that value of θ. The modified likelihood, which may be called $p(\theta)$ is then

$$p(\theta)=f(\theta)L(\theta)/\int[f(\theta)L(\theta)]d\theta. \qquad [1]$$

Equation 1 is called the posterior probability density function. Just as the maximum likelihood score is the value of θ for which $L(\theta)$ is maximum, one kind of Bayesian score is the value of θ for which $p(\theta)$ is maximum. Such scores are called Bayes modal estimates by Samejima (1969) because they are based on the mode of the posterior density function. A different type of Bayesian estimate is based on the mean of the posterior density function. Owen's (1975) Bayesian scoring procedure, which will be described in detail below, is an example of this approach. In his procedure, the prior probability densities are provided by a normal density function. Other Bayesian scoring procedures are also available (Sympson, 1977).

These concepts can be illustrated using the likelihoods associated with the [1,0] response pattern discussed earlier. Table 2 shows for several values of θ the probability of a correct response to the first item [$P_1(\theta)$]; the probability of an incorrect response to the second item [$Q_2(\theta)$]; the likelihood of the response pattern [$L(\theta)$] (these first three columns correspond to the data in Table 1); the prior probability densities [$f(\theta)$], which in this case are ordinates of a normal distribution with mean of zero and standard deviation of 1; and the posterior density function [$p(\theta)$], computed using Equation 1. For these data

$$\int [f(\theta)L(\theta)]d\theta \simeq .348. \qquad [2]$$

The resulting posterior density function, [$p(\theta)$], is shown as the dashed curve in Figure 2.

Table 2
Response Probabilities [$P_1(\theta)$, $Q_2(\theta)$], Likelihoods [$L(\theta)$], Weights [$w(\theta)$], and Posterior Density Function [$p(\theta)$] for a Two-Item Response Pattern

θ	$P_1(\theta)$	$Q_2(\theta)$	$L(\theta)$	$f(\theta)$	$p(\theta)$
-3.0	.187	.780	.146	.004	.002
-2.5	.212	.780	.165	.018	.009
-2.0	.257	.779	.200	.054	.031
-1.5	.332	.776	.257	.130	.096
-1.0	.442	.768	.340	.242	.236
-0.5	.580	.742	.430	.352	.435
0.0	.718	.668	.479	.399	.549
0.5	.828	.503	.416	.352	.421
1.0	.903	.277	.250	.242	.174
1.5	.948	.112	.106	.130	.040
2.0	.973	.038	.037	.054	006
2.5	.986	.012	.012	.018	.001
3.0	.993	.004	.004	.004	.000

The mode of the posterior density function in Figure 2 is located near $\theta=0$, so the Bayesian modal estimate and the maximum likelihood estimate are about the same for this data. The Bayesian θ estimate based on the mean of the $p(\theta)$ distribution is -.12. This θ estimate does not coincide with the maximum likelihood estimate ($\hat{\theta}=.01$); as will be further shown below, estimates of θ obtained from different ICC scoring methods do not generally agree.

Differences Among Scoring Methods

The programs described in this report are capable of scoring test data using most of the ICC response models available. The selection among models should not be arbitrary, especially when individual decisions are to be made on the basis of test scores. Dichotomous data can be scored by means of the one-, two-, and three-parameter ICC models, using either a normal or logistic ogive ICC. Thus, given the decision with regard to the number of parameters that describe the ICC, there still remains the problem of choosing between the normal or logistic ogive response models for scoring purposes. Unfortunately, there are as yet no firm guidelines for choosing between these two response models. Samejima (1969) has shown that the normal and logistic ogive models differ with respect to their scoring "philosophies," but the practical implications of these differences remain to be investigated.

To illustrate the differences among the models and different ICC scoring procedures, all response patterns for a five-item test were scored by maximum likelihood, assuming both normal and logistic ogive ICCs, and by Owen's (1975) Bayesian scoring method. Table 3 gives the item parameters assumed for the hypothetical five-item test. For all items, the c (guessing) parameter was set at 0.0, indicating that a two-parameter ICC model was used. Items varied in difficulty (b) from -2 to +2 and had discriminations of 1.00 or 1.50.

Table 3
Item Paremeters for Five-Item Test

Item	a	b	c
1	1.00	-2.00	.00
2	1.50	-1.00	.00
3	1.00	0.00	.00
4	1.50	1.00	.00
5	1.00	2.00	.00

In a five-item test in which each item is scored dichotomously, there are $2^5=32$ different response patterns. These response patterns are shown in Table 4 along with the scores associated with them. It is obvious from the data in Table 4 that for a given response pattern, the scores (all of which are on the same metric) differed somewhat. This indicates that the scoring procedures are not interchangeable.

For example, consider the five response patterns which have 20% correct, namely Patterns 2, 3, 5, 9, and 17. Not only do the θ estimates (scores) for a given response pattern differ among the three scoring procedures, but there are some differences in the ordering of the θ estimates derived from these response patterns within each procedure. For maximum likelihood scoring using

a normal ogive ICC, the ordering of the θ estimates derived from the five response patterns was exactly the same as that obtained from the Bayesian scoring procedure, although the numerical values of the θ estimates were uniformly higher for the Bayesian procedure. For both these scoring methods, there was a tendency for higher ability estimates to be obtained when a more difficult item was answered correctly. For example, the lowest θ estimate was obtained by both scoring methods when the easiest item (Item 1) was answered correctly (Response Pattern 17); when only Item 2 was answered correctly (Response Pattern 9), the θ estimates from both the Bayesian and maximum likelihood normal procedures increased. In addition, both scoring methods took into account the discriminations of the items involved. For example, Response

Table 4

Scores Given to Each Response Pattern by Three Scoring Methods

Response Pattern	Maximum Likelihood Normal	Maximum Likelihood Logistic	Bayesian
1. 00000	∞*	∞*	-1.72
2. 00001	-.93	-1.60	-.64
3. 00010	-.61	-1.19	-.38
4. 00011	-.13	-.46	.11
5. 00100	-1.42	-1.60	-1.06
6. 00101	-.50	-.84	-.28
7. 00110	-.30	-.46	-.11
8. 00111	.13	.46	.30
9. 01000	-1.24	-1.19	-.89
10. 01001	-.23	-.46	-.15
11. 01010	.03	.00	.00
12. 01011	.50	.84	.41
13. 01100	-.60	-.46	-.42
14. 01101	.23	.46	.17
15. 01110	.39	.84	.28
16. 01111	.93	1.60	.64
17. 10000	-1.63	-1.60	-1.16
18. 10001	-.39	-.84	-.24
19. 10010	-.17	-.46	-.06
20. 10011	.30	.46	.39
21. 10100	-.78	-.84	-.58
22. 10101	.03	.00	.11
23. 10110	.17	.46	.23
24. 10111	.61	1.19	.62
25. 11000	-.42	-.46	-.29
26. 11001	.60	.46	.51
27. 11010	.78	.84	.63
28. 11011	1.42	1.60	1.09
29. 11100	.42	.46	.31
30. 11101	1.24	1.19	.93
31. 11110	1.63	1.60	1.08
32. 11111	∞*	∞*	1.55

*For maximum likelihood scoring, it is not possible to score response patterns with all correct or incorrect answers.

Pattern 2 (with a correct response to Item 5, the most difficult item) was assigned higher scores than Pattern 5; but Pattern 2 was assigned lower scores than Pattern 3 (which had a correct response to Item 4, the second most difficult item), since in Response Pattern 3 a correct answer was given to an item (Item 4) with a higher discrimination than that of Pattern 2 (Item 5).

On the other hand, assuming a logistic ogive ICC for the maximum likelihood scoring procedure, estimated values of θ were related to the discriminations of the items answered correctly. Those response patterns for which the discriminations of the items answered correctly were the same were assigned the same score, namely -1.60 for Patterns 2, 5, and 17 and -1.19 for Patterns 3 and 9. For the latter two response patterns, the discriminations of the items answered correctly were 1.50; for the former three response patterns, they were 1.00. Thus, the magnitude of the scores was a function of the item discriminations, and the item difficulties did not affect the θ estimates.

These data indicate that the assumption of different forms of the ICC within the maximum likelihood scoring procedure will, in general, result in different θ estimates. Since the Bayesian θ estimates were different from both the maximum likelihood estimates, these three ICC-based scoring procedures are not interchangeable. However, additional research is required to further delineate the similarities and differences among the θ estimates derived by different ICC-based scoring procedures and, more importantly, to assess the implications of these differences in practical applications.

General Description of the Programs

This report describes three computer programs for scoring test data with ICC models--LINDSCO, ADADSCO, and LINPSCO. Table 5 summarizes the major features of these programs. LINDSCO (LINear Dichotomous SCOring) is designed

Table 5
Summary of Program Capabilities

Model and Scoring Procedure	Dichotomous: Linear (LINDSCO)	Dichotomous: Adaptive (ADADSCO)	Polychotomous (LINPSCO): Graded	Polychotomous (LINPSCO): Nominal
Logistic Ogive				
Bayesian[a]	NO	NO	NO	NO
Maximum Likelihood	YES	YES	YES	YES
Normal Ogive				
Bayesian[a]	YES	YES	NO	NO
Maximum Likelihood	YES	YES	YES	NO

[a]The Bayesian scoring procedure is based on Owen (1975).

to be used for scoring test data for conventional (linear) tests in which all items are administered to each testee. It requires responses to be dichotomous; that is, responses are scored into one of two categories, such as "correct"

and "incorrect." Omissions are permitted, but they are ignored in the computations. The number of omitted items is tallied from the number of items administered and reported as part of the output for each testee. Either the normal or logistic ogive response model can be used with ICCs described by one, two, or three parameters for maximum likelihood scoring. Response patterns may also be scored by Owen's (1975) Bayesian method which assumes a normal ogive ICC. The user can also specify, in addition to a total test score, subscores on as many as 25 subscales.

ADADSCO (ADAptive Dichotomous SCOring) is similar to LINDSCO, but it is designed specifically for scoring item response data derived from adaptive testing. Since in adaptive testing each respondent answers a different set of test items, the program must locate for each testee the item parameter estimates of each attempted item; LINDSCO, in contrast, does the item search only once. ADADSCO also differs from LINDSCO in that it has no subscale scoring capabilities.

LINPSCO (LINear Polychotomous SCOring) is designed to score data from linear (conventional) tests in which each testee is administered all items, and items are scored into more than two categories. Three models are available: the graded normal and logistic ogive models (Samejima, 1969), and the nominal logistic model (Bock, 1972). In LINPSCO only maximum likelihood scoring is available, and subscale scoring is not possible.

All three programs compute both test information and response pattern information values when maximum likelihood scoring is used. Response pattern information (Samejima, 1973) provides an estimate of the precision of measurement for a specified response pattern and can be used to compare the quality of trait estimates derived from specific test administration and/or scoring procedures (e.g., Bejar, Weiss, & Gialluca, 1977).

NUMERICAL PROCEDURES

Dichotomous Data

Maximum Likelihood

The numerical procedure for maximum likelihood scoring of dichotomous data consists of two stages. In the first stage an initial estimate is sought by the bisection method. Once this initial estimate is obtained, it is refined further by the Newton-Raphson method.

The bisection routine begins in the interval ±5.00. If the sign of the first derivative of the likelihood function during the first iteration is the same when evaluated at 5.00 and at -5.00, a value of 0.0 is returned as the initial estimate of θ. Otherwise, five additional iterations are performed. After the sixth iteration, the width of the interval has been reduced to $10/(2^6) = 10/64 = .15$. The midpoint of that interval is the initial estimate which is then refined further by Newton-Raphson iterations of the form:

$$\hat{\theta}_{m+1} = \hat{\theta}_m - (f'/f'') \quad , \qquad [3]$$

where

$\hat{\theta}_{m+1}$ is the new estimate,

$\hat{\theta}_m$ is the estimate from the last iteration,

f' is the first derivative of the log-likelihood function evaluated at $\hat{\theta}_m$, and

f'' is the second derivative of the log-likelihood function evaluated at $\hat{\theta}_m$.

This iterative process is continued until $|\hat{\theta}_{m+1} - \hat{\theta}_m| < .005$. If that criterion has not been met at the end of 50 iterations, the case is said to be nonconvergent.

Formulas for derivatives. Let $v = \{u_g, g=1, 2, \ldots n\}$ be a response vector such that

$$u_g = \begin{cases} 1 \text{ if the item is answered correctly} \\ 0 \text{ if the item is answered incorrectly.} \end{cases}$$

Note that for scoring purposes, the response vector does not include rejected or omitted items. The probability that $u_g=1$ for a given value of θ and item parameters a_g, b_g, and c_g is given by

$$P_g(\theta) = c_g + (1-c_g)[1 + e^{-1.7a_g(\theta - b_g)}]^{-1} \qquad [4]$$

for the logistic ogive model and by

$$P_g(\theta) = c_g + (1-c_g) \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{a_g(\theta-b_g)} e^{t^2/2} dt$$

$$= c_g + (1-c_g)\ \Phi\ [a_g(\theta-b_g)] \qquad [5]$$

for the normal ogive model, where Φ stands for the standard cumulative normal distribution.

The log-likelihood function for the response vector is

$$L_v(\theta) = \sum_g \log P_g(\theta)^{u_g}\ Q_g(\theta)^{1-u_g}$$

$$= \sum_g [u_g \log P_g(\theta) + (1-u_g) \log Q_g(\theta)] \qquad [6]$$

where $Q_g(\theta) = 1-P_g(\theta)$ and $P_g(\theta)$ is given by either Equation 4 or 5.

In general, the first and second derivatives of the log-likelihood function of a response vector are given by

$$\frac{\partial L_v(\theta)}{\partial\theta} = \sum_g \left\{ u_g \left[\left(\frac{1}{P_g(\theta)}\right)\left(\frac{\partial P_g(\theta)}{\partial\theta}\right)\right] + (1-u_g)\left[\left(\frac{1}{Q_g(\theta)}\right)\left(\frac{\partial Q_g(\theta)}{\partial\theta}\right)\right]\right\} \qquad [7]$$

and

$$\frac{\partial^2 L_v(\theta)}{\partial\theta^2} = \sum_g \left\{ u_g \left[\left(\frac{1}{P_g^2(\theta)}\right)\left(\frac{\partial P_g(\theta)}{\partial\theta}\right)^2 - \left(\frac{1}{P_g(\theta)}\right)\left(\frac{\partial^2 P_g(\theta)}{\partial\theta}\right)\right]\right.$$

$$\left. + (1-u_g)\left[\left(\frac{1}{Q_g^2(\theta)}\right)\left(\frac{\partial Q_g(\theta)}{\partial\theta}\right)^2 + \left(\frac{1}{Q_g(\theta)}\right)\left(\frac{\partial^2 Q_g(\theta)}{\partial\theta^2}\right)\right]\right\}. \qquad [8]$$

For the logistic ogive model, after simplification and letting $x = 1.7a_g(\theta-b_g)$, these expressions are

$$\frac{\partial L_v(\theta)}{\partial\theta} = -1.7\sum_g \left[\frac{a_g e^x}{1+e^x}\right] + 1.7\sum_g \left[\frac{u_g a_g e^x}{c_g + e^x}\right] \qquad [9]$$

and

$$\frac{\partial^2 L_v(\theta)}{\partial\theta^2} = -2.89\sum_g \left[\frac{a_g^2 e^x}{(1+e^x)^2}\right] + 2.89\sum_g \left[\frac{u_g a_g^2 c_g e^x}{(c_g+e^x)^2}\right]. \qquad [10]$$

For the normal ogive model, letting $x = -a_g^2(\theta-b_g)^2/2$, the corresponding expressions are

$$\frac{L_v(\theta)}{\partial\theta} = \sum_g \left[\frac{u_g(2\pi)^{-1/2}a_g(1-c_g)e^x}{c_g+(1-c_g)\Phi[a_g(\theta-b_g)]} - \frac{(1-u_g)(2\pi)^{-1/2}(1-c_g)a_g e^x}{1-\{c_g+(1-c_g)\Phi[a_g(\theta-b_g)]\}}\right] \qquad [11]$$

and

$$\frac{\partial^2 L_v(\theta)}{\partial\theta^2} = \sum_g \left\{ u_g \left[- \frac{[(2\pi)^{-1/2}(1-c_g)a_g e^x]^2}{\{[c_g-(1-c_g)\Phi[a_g(\theta-b_g)]]\}^2} - \frac{(2\pi)^{-1/2}a_g^3(\theta-b_g)(1-c_g)e^x}{\{c_g-(1-c_g)\Phi[a_g(b_g-\theta)]\}} \right] + \right.$$

$$\left. \sum_g (1-u_g) \left[- \frac{[(2\pi)^{-1/2}(1-c_g)a_g e^x]^2}{1-\{c_g+(1-c_g)\Phi[a_g(\theta-b_g)]\}^2} + \frac{(2\pi)^{-1/2}a_g^3(\theta-b_g)(1-c_g)e^x}{1-\{c_g+(1-c_g)\Phi[a_g(\theta-b_g)]\}} \right] \right\} \quad [12]$$

Computation of information. With maximum likelihood scoring, two measures of information are computed for each response pattern. One is response pattern information (Samejima, 1973) denoted by $\hat{I}(\hat{\theta})$; the other is test information (Birnbaum, 1968; Samejima, 1969) denoted by $I(\hat{\theta})$. Test information is defined as the expected value of the second derivative of the log-likelihood function, i.e.,

$$I(\hat{\theta}) = -\sum_g \left[E \left\{ \frac{\partial^2 \log L_v(\theta)}{\partial\theta^2} \right\} \right] . \quad [13]$$

Response pattern information, on the other hand, is defined by

$$\hat{I}(\hat{\theta}) = -\sum_g \left[\frac{\partial^2 \log L_v(\theta)}{\partial\theta^2} \right] , \quad [14]$$

that is, the "observed," as opposed to expected, value of the second derivative of the log-likelihood function evaluated at $\hat{\theta}$.

These two measures of information will be the same for models in which there is a sufficient statistic for the response vector. In particular, this is true in the one- and two-parameter logistic ogive models. It is also true for the "zero" parameter normal ogive model, i.e., when the items are parallel. The value of $\hat{I}(\hat{\theta})$ for a given response pattern is simply the value of the second derivative of the log-likelihood function at the last iteration, i.e., evaluated at the estimated value of θ.

$I(\hat{\theta})$ is computed by

$$I(\hat{\theta}) = \sum_g \frac{\{P_g'(\hat{\theta})\}^2}{P_g(\hat{\theta})\{1.0-P_g(\hat{\theta})\}} , \quad [15]$$

where $P_g(\theta)$ is given, in general, by Equation 4 for the logistic ogive model and by Equation 5 for the normal ogive model.

For the normal ogive model,

$$P'_g(\hat{\theta}) = \frac{a_g(1-c_g)}{\sqrt{2\pi}} \left[e^{-a_g^2[\theta-b_g]^2/2}\right] \quad ; \qquad [16]$$

and for the logistic ogive model,

$$P'_g(\hat{\theta}) = \frac{1.7a_g(1-c_g)e^{1.7a_g(\hat{\theta}-b_g)}}{[1+e^{1.7a_g(\hat{\theta}-b_g)}]^2} \quad . \qquad [17]$$

Standard error. The standard error of measurement associated with $\hat{\theta}$ is computed as $1/\sqrt{I(\hat{\theta})}$, that is, the reciprocal square root of response pattern information evaluated at $\hat{\theta}$.

Bayesian Scoring

The Bayesian scoring procedure used by LINDSCO and ADADSCO is derived from Owen's (1975) sequential adaptive testing strategy. However, since the present application assumes that the test items have already been administered, only the scoring aspect is of interest.

The procedure makes the assumption that the prior distribution of θ is normal, with mean $\mu_\circ$=0.0 and variance $\sigma_\circ^2$=1.00, where subscript $_\circ$ denotes the fact that no items have yet been administered. After the m^{th} item is administered, the mean and variance of the posterior density function are computed according to the following equations. If the response to the $m + 1^{th}$ item is correct,

$$\mu_{m+1} = E(\theta|1) = \mu_m+(1-c_g)\left(\frac{\sigma^2_m}{\sqrt{\frac{1}{a^2_g} + \sigma^2_m}}\right)\left(\frac{\phi(D)}{c_g+(1-c_g)\Phi(-D)}\right) \qquad [18]$$

and

$$\sigma^2_{m+1} = \text{var}(\theta|1) = \sigma^2_m \left\{ 1-\left(\frac{1-c_g}{1+\frac{1}{a^2_g\sigma^2_m}}\right)\left(\frac{\phi(D)}{A}\right)\left(\frac{(1-c_g)\phi(D)}{A} - D\right)\right\} . \qquad [19]$$

Following an incorrect answer,

$$\mu_{m+1} = E(\theta|0) = \mu_m - \left(\frac{\sigma^2_m}{\sqrt{\frac{1}{a^2_g} + \sigma^2_m}}\right)\left(\frac{\phi(D)}{\Phi(D)}\right) \qquad [20]$$

and

$$\sigma^2_{m+1} = \mathrm{var}(\theta|0) = \sigma^2_m \left\{1 - \left(\frac{\phi(D)}{1 + \frac{1}{a^2_g \sigma^2_m}}\right)\left(\frac{\frac{\phi(D)}{\Phi(D)} + D}{\Phi(D)}\right)\right\}. \qquad [21]$$

In Equations 18 through 21 (from Owen, 1975),

$\phi(D)$ is the normal probability density function,
$\Phi(D)$ is the cumulative normal distribution function,

$$D = \frac{b_g - \mu_m}{\sqrt{\frac{1}{a^2_g} + \sigma^2_m}}\text{ , and} \qquad [22]$$

$$A = c_g + (1-c_g)\ \Phi\ (-D)\,. \qquad [23]$$

After the last item has been administered, the posterior mean is the estimated θ and the posterior variance is a measure of the error associated with that estimate. Because the posterior distribution after every item is administered is approximated by a normal distribution in this procedure, there is a certain amount of inaccuracy in the estimate. Moreover, the resulting scores are order dependent (Sympson, 1977), i.e., if a response vector were to be scored after rearranging the items, the resulting θ estimate would be slightly different.

Computation of Expected Proportion of Correct Answers

The expected proportion of correct answers (EXPTOT) is defined as

$$\text{EXPTOT} = \Sigma_g P_g(\hat{\theta})/NI\ , \qquad [24]$$

where $P_g(\hat{\theta})$ is computed from Equation 4 for the logistic ogive model and Equation 5 for normal ICCs. NI is the number of items on which the estimate of θ is based. EXPTOT is simply an estimate of the true score associated with $\hat{\theta}$ (Lord & Novick, 1968, p. 387).

Polychotomous Data

LINPSCO is capable of scoring polychotomous data when item parameters have been estimated according to a graded model of either normal or logistic ogive form (Samejima, 1969) or according to Bock's (1972) nominal logistic model. For the graded model, the numerical procedure consists of a bisection stage of six iterations followed by Newton-Raphson iterations. For the nominal logistic model, the initial estimate obtained from the bisection stage is refined further by the secant method rather than by Newton-Raphson iterations.

In each case, the bisection phase begins in the interval ±5.00. During the first iteration, if the sign of the first derivative of the log-likelihood function is the same when evaluated at 5.00 and at -5.00, a value of 0.0 is returned as the initial estimate. Otherwise, five additional iterations are performed. After six iterations, the width of the interval is reduced to $10/(2^6)=10/64=.15$. The midpoint of that interval is taken as the initial estimate.

The Newton-Raphson procedure used with the graded models refines the initial estimate with iterations of the form shown in Equation 3. This iterative procedure is continued until $|\hat{\theta}_{m+1} - \hat{\theta}_m|$ is less than .005 or the number of iterations is greater than 50. The secant procedure is similar to Newton-Raphson iterations, except that f'' in Equation 3 is an approximation to the second derivative of the log-likelihood function given by

$$f'' = \frac{f'(\hat{\theta}_m)-f'(\hat{\theta}_{m-1})}{(\hat{\theta}_m - \hat{\theta}_{m-1})} \quad . \qquad [25]$$

Graded Models

Let $v = \{x_g, g=1, 2, \ldots\}$ be a response vector exclusive of omitted and rejected items such that

$$x_g = \begin{cases} 1 = \text{if the "best response was given} \\ 2 = \text{if the second "best" response was given} \\ \cdot \\ \cdot \\ \cdot \\ m_g-1 \text{ if the next to worst response was given} \\ m_g \text{ if the worst response was given.} \end{cases}$$

For the graded logistic ogive model, the probability that x_g takes one of the values between 1 and m_g is given in general by

$$P_{x_g}(\theta) = P_{x_g} = [1 + e^{y_{x_g}}]^{-1} - [1+e^{y_{x_g-1}}]^{-1} \quad , \qquad [26]$$

where

$$y_{x_g} = -a_g D(\theta - b_{x_g}) \quad , \qquad [27]$$

$$y_{x_g - 1} = -a_g D(\theta - b_{x_g - 1}) \text{ , and} \qquad [28]$$

$D = 1.7$ is a scaling factor.

When $x_g = 1$,

$$P_{x_g} = [1 + e^{y_{x_g}}]^{-1} \ . \qquad [29]$$

When $x_g = m_g$,

$$P_{x_g} = 1 - [1 + e^{y_{x_g - 1}}]^{-1}. \qquad [30]$$

For the graded normal ogive model, the probability that x_g takes one of the values between 1 and m_g is given in general by

$$P_{x_g}(\theta) = P_{x_g} = (2\pi)^{-\frac{1}{2}} \int_{y_{x_g - 1}}^{y_{x_g}} e^{t^2/2} dt$$

$$\doteq \Phi\left[y_{x_g}\right] - \Phi\left[y_{x_g - 1}\right] \quad , \qquad [31]$$

where

$$y_{x_g} = a_g(\theta - b_{x_g}) \qquad [32]$$

and

$$y_{x_g - 1} = a_g(\theta - b_{x_g - 1}) \quad . \qquad [33]$$

When $x_g = 1$,

$$P_{x_g} = (2\pi)^{-1} \int_{-\infty}^{y_{x_g}} e^{t^2/2} dt \ . \qquad [34]$$

When $x_g = m_g$,

$$P_{x_g} = 1 - (2\pi)^{-1} \int_{-\infty}^{y_{x_g}-1} e^{t^2/2} dt \quad . \qquad [35]$$

The log-likelihood function for a given response vector is given by

$$L_v(\theta) = \log \prod_g P_{x_g}^{r_{x_g}}$$

$$= \sum_g r_{x_g} [\log P_{x_g}] \ , \qquad [36]$$

where

$$r_{x_g} = \begin{cases} 1 \text{ if the } x_g^{\text{th}} \text{ response category is chosen} \\ 0 \text{ otherwise} \ . \end{cases}$$

The general first derivative of the log-likelihood function is

$$\frac{\partial L_v(\theta)}{\partial \theta} = \sum_g \sum_{x_g} r_{x_g} L_{x_g} \quad . \qquad [37]$$

Samejima (1969) referes to L_{x_g} as the basic function. Since $L_{x_g} = (\partial P_{x_g}/\partial\theta)(P_{x_g})^{-1}$

$$\frac{\partial L_v(\theta)}{\partial \theta} = \sum_g \sum_{x_g} r_{x_g} \frac{\partial P_{x_g}/\partial\theta}{P_{x_g}} \quad . \qquad [38]$$

The general second derivative of the log-likelihood function is given by

$$\frac{\partial^2 L_v(\theta)}{\partial \theta^2} = \sum_g \sum_{x_g} r_{x_g} [-(L_{x_g})^2 + \frac{\partial^2 P_{x_g}/\partial\theta^2}{P_{x_g}}] \quad . \qquad [39]$$

Specifically, for the graded logistic ogive model,

$$\frac{\partial L_v(\theta)}{\partial \theta} = \sum_g \sum_{x_g} a_g 1.7\{1-P^*_{x_g} - P^*_{x_g-1}\} \qquad [40]$$

and

$$\frac{\partial^2 L_v(\theta)}{\partial\theta^2} = \sum_g \sum_{x_g} 2.89 a_g^2 \frac{r_{x_g}}{P_{x_g}} \left[-\left\{ (L_{x_g})^2 + (2Q^*_{x_g-1})(P^*_{x_g} Q^*_{x_g}) - \right.\right.$$

$$\left.\left. (2Q^*_{x_g-1} - 1)(P^*_{x_g-1} Q^*_{x_g-1}) \right\} \right] , \qquad [41]$$

where

$$P^*_{x_g} = [1 + e^{-1.7a_g(\theta - b_{x_g})}]^{-1} , \qquad [42]$$

$$P^*_{x_g-1} = [1 + e^{-1.7a_g(\theta - b_{x_g-1})}]^{-1} , \qquad [43]$$

$$P^*_o = 0 , \qquad [44]$$

$$P^*_{m_g} = 1 , \qquad [45]$$

$$Q^*_{x_g} = 1 - P^*_{x_g} , \text{ and} \qquad [46]$$

$$Q^*_{x_g-1} = 1 - P_{x_g-1} . \qquad [47]$$

For the graded normal ogive model, letting $z_{x_g} = -[a_g^2(\theta - b_{x_g})^2] / 2$, the corresponding expressions are

$$\frac{\partial L_v(\theta)}{\partial\theta} = \sum_g \left[\sum_{x_g} \left(\frac{r_{x_g} a_g}{\sqrt{2\pi}} [e^{z_{x_g}} - e^{z_{x_g-1}}] \right) / P_{x_g}(\theta) \right] \qquad [48]$$

The second derivative is given by

$$\frac{\partial^2 L_v(\theta)}{\partial\theta^2} = \sum_g \left\{ \sum_{x_g} r_{x_g} \left[-(L_{x_g})^2 \right] + \right.$$

$$\left. \left[\frac{-a_g^3}{\sqrt{2\pi}} \{(\theta - b_{x_g}) e^{z_{x_g}} - (\theta - b_{x_g-1}) e^{z_{x_g-1}}\} \right] / P_{x_g}(\theta) \right\} \qquad [49]$$

When $x_g=1$, $e^{z_{x_g-1}}=0$, and P_{x_g} is given by Equation 34; when $x_g=m_g$, $e^{z_{x_g}}=0$, and P_{x_g} is given by Equation 35.

Nominal Logistic Model

For the nominal logistic model, the probability of x_g, given θ, is given by

$$P_{x_g}(\theta) = P_{x_g} = e^{(\alpha_{x_g}\theta+\beta_{x_g})} / \sum_{s=1}^{m_g} e^{(\alpha_s\theta+\beta_s)} , \qquad [50]$$

where α_s and β_s are the slope and intercept parameter for the s^{th} response category.

The secant method requires only the first derivative of the log-likelihood function. That derivative is

$$\frac{\partial L_v(\theta)}{\partial\theta} = \sum_g \frac{\sum_{s=1}^{m_g} r_{x_g}(\alpha_{x_g}-\alpha_s)e^{\alpha_s\theta+\beta_s}}{\sum_{s=1}^{m_g} e^{(\alpha_s\theta + \beta_s)}} . \qquad [51]$$

Computation of Information

Response pattern information is computed as the value of the second derivative at the last iteration. For the nominal logistic model, that value is an approximation. Test information is computed from the general formula given by Samejima (1969),

$$I(\hat{\theta}) = \sum_g \sum_{x_g} (\partial P_{x_g}/\partial\theta)^2 P_{x_g} . \qquad [52]$$

This expression involves only the first derivative of the response model. The appropriate expressions are listed below.

For the graded normal ogive model,

$$\frac{\partial P_{x_g}}{\partial\theta} = \frac{a_g}{\sqrt{2\pi}}\left[e^{z_{x_g}} - e^{z_{x_g-1}}\right] , \qquad [53]$$

where $z_{x_g} = -[a_g^2(\theta-b_{x_g})^2] /2$.

For the graded logistic ogive model,

$$\frac{\partial P_{x_g}}{\partial \theta} = 1.7\, a_g [P^*_{x_g}(1-P^*_{x_g}) - P^*_{x_g-1}(1-P^*_{x_g-1})] \,, \qquad [54]$$

where $P^*_{x_g} = [1+e^{-1.7a(\theta - b_{x_g})}]^{-1}$.

For the nominal logistic model,

$$\frac{\partial P_{x_g}}{\partial \theta} = \frac{[e^{(\alpha_{x_g}\theta + \beta_{x_g})} \sum_{s=1}^{m_g} e^{(\alpha_{s_g}\theta + \beta_{s_g})} (\alpha_{x_g} - \alpha_s)]}{\sum_{s=1}^{m_g} e^{(\alpha_{s_g}\theta + \beta_{s_g})^2}} \,. \qquad [55]$$

USE OF THE PROGRAMS

Input

For each of the programs, three types of input are required:

1. The *Program Parameters*, which consist of specifications as to the number of items in the pool, the options chosen, the scoring key, and so forth.
2. The *Item Pool*, which contains the item parameter estimates on as many as 600 items for LINDSCO and ADADSCO, and 100 items for LINPSCO.
3. The *Test Response Data* consists of testee name and identification number and each testee's item responses. For LINDSCO, item responses need not be dichotomized beforehand; for ADADSCO, they must be dichotomized unless a key is provided as part of the item pool. For ADADSCO, the number of items attempted and the identification number of each item attempted must also be supplied as part of the test response data. For LINPSCO, the test response data must be supplied in such a way that the first category corresponds to the "best" response, while the last category corresponds to the "worst" response, based on previously obtained item parameterization data.

Testee response data containing all correct or incorrect answers cannot be scored by maximum likelihood. If such a response pattern is found, a message is printed, and the estimated θ is set to 10.00 if all responses are correct and to -10.00 if all responses are incorrect. The information is set to 0.0 in both cases. Response patterns with all answers correct or incorrect present no problem for Bayesian scoring, and they are processed normally; however, a message is still printed. Appendix B gives examples of the use of each of these programs.

Table 6
Input Program Parameters for LINDSCO, ADADSCO, and LINPSCO: Card Set 1

Columns	LINDSCO	ADADSCO	LINPSCO
1-4 (I4)	INUP, number of items in item pool. 600 is the maximum.	INUP, same as LINDSCO	Number of items in the pool. Maximum is 100.
5-8 (I4)	M, number of items in test. 300 is the maximum	MMAX, maximum number of items administered. 60 is the maximum.	M, number of items in the test. Maximum is 50.
9	blank	blank	blank
10 (I1)	OPT1 1 = Punch the item parameter estimates corresponding to the items in the test.	OPT1 1 = Print the item parameter estimates corresponding to the items administered (this is done only for the first 10 testees).	OPT1 1 = Punch the item parameter estimates corresponding to the items in the test.
11 (I1)	OPT2 1 = the item pool consists of M items, i.e., there will be no searching of items in the pool.	not used	OPT2 1 = the item pool consists of M items, i.e., there will be no searching of items in the pool.
12 (I1)	OPT3 If 1, 2, or 3 item parameters will be edited; see "Editing of item parameters."	OPT3, same as LINDSCO	not used
13 (I1)	OPT4, scoring algorithms and response model: 1 = maximum likelihood normal ogive 2 = maximum likelihood logistic 3 = Owen's Bayesian normal ogive	OPT4, same as LINDSCO	OPT4, response model: 1 = graded logistic ogive 2 = graded normal ogive 3 - nominal logistic

14-18 (F5.2)	TS, for Bayesian scoring. This is the prior mean of θ. Not used in maximum likelihood scoring.	TS, same as LINDSCO	D, scaling parameter for graded logistic model. If blank, will be set by default to 1.0; otherwise will usually be set by the user to 1.7.
19-23 (F5.2)	TSS, for Bayesian scoring. This is the prior standard deviation of θ. Not used in maximum likelihood scoring.	TSS, same as LINDSCO	not used
24-28 (F5.2)	AMAX, value of the a parameter. Used in editing. See "Editing of item parameters."	AMAX, same as LINDSCO	not used
29-33 (F5.2)	BMIN, lowest value of the b parameter. Used in editing parameter estimates. See "Editing of item parameters."	BMIN, same as LINDSCO	not used
34-38 (F5.2)	BMAX, highest value of the b parameter. Used in editing parameter estimates. See "Editing of item parameters."	BMAX, same as LINDSCO	not used
39-43 (F5.2)	CMAX, value of the c parameter. Used in editing parameter estimates. See "Editing of item parameters."	CMAX, same as LINDSCO	not used
44-45 (I2)	blank	IFLAG, code for correct response	
46-47 (I2)	IOMIT, code for omitted response.	IOMIT, same as LINDSCO	IOMIT, same as LINDSCO
48-80	blank	blank	blank

Program Parameters

Table 6 describes the input program parameters for all three programs, using Card Set 1 (all numeric information is right justified). After Card Set 1, the program parameter and input for each of the three programs differs, as indicated below.

LINDSCO (Card Set 2-10).

Card Set 2 (8A10). The variable format for the item pool is punched on this card, using I-fields (see Item Pool below).

Card Set 3 (16I5). Punch in five-column fields the item identification number of the items in the test in the same order in which they appear in the test. Continue on as many cards as necessary.

Card Set 4 (80I1). A "1" in a given column is punched to omit a specified item from all computations, e.g., if the 10th item is to be omitted, punch "1" in column 10; if the 100th item is to be omitted, punch "1" in column 20 of the second card. Continue on as many cards as necessary.

Card Set 5 (80I1). This card contains the scoring key for the test. In general, the n^{th} column contains the key for the n^{th} item, as in Card Set 4. Continue on as many cards as necessary.

Card Set 6 (8A10). Variable format for reading the subject information and test response data (see Test Response Data below for field type specifications).

Card Set 7 (8A10). The description of the run is written on three cards. The three cards must be included even if they are blank.

Card 8 (I5). Punch the number of subscales to be scored in columns 1-5; maximum is 25. If no subscales are to be scored, punch "0" in column 5; in that case, this is the last card set.

Card Set 9 (2I5). (Omit if the number of subscales is 0.) For each scale, punch the following information:
Columns 1-5: Number of items in subscale (maximum is 60).
Columns 6-10: Scale number. Repeat for each subscale beginning on a new card.

Card Set 10 (16I5). (Omit if the number of subscales is 0.) Punch in five-column fields the item identification number of the items in the subscales. Continue on as many cards as necessary. Repeat for each subscale, beginning on a new card for each subscale.

ADADSCO (Card Set 2-5).

Card Set 2 (8A10). Variable format for item pool, using I-fields. It must be contained on one card (see Item Pool below).

Card Set 3 (16I5). Columns 1-5: The number of items to be omitted, i.e., excluded from the computations. If none, punch "0" in column 5.

Columns 6-10 and subsequent five-column fields: The item identification numbers of items to be omitted. Continue on as many cards as necessary. If more than one card is necessary, begin punching on the second card in columns 1-5.

Card Set 4 (8A10). Variable input format for reading subject information and test response data. It must be contained on one card (see Test Response Data below for field type specifications).

Card Set 5 (8A10). Description of the run is written on three cards. These cards are required, even if they are left blank.

LINPSCO (Card Set 2-7).

Card Set 2 (8A10). Variable format for the item pool. It must be contained on one card (see Item Pool below for field type specifications).

Card Set 3 (80I1). Punch in the n^{th} column the number of response categories minus 1 for the n^{th} item. Continue on as many cards as necessary.

Card Set 4 (16I5). Punch in five-column fields the item identification numbers of the items in the test. The numbers must appear in the same order as the items appear in the test. Continue on as many cards as necessary.

Card Set 5 (80I1). The information on this card is used to omit specified items from the computations. To omit the n^{th} item, punch a "1" in the n^{th} column of this card; otherwise, punch "0." If no items are to be omitted, punch as many zeros as there are items in the test. Continue on as many cards as necessary.

Card Set 6 (8A10). Variable format for subject information and test response data. It must be contained on one card (see Test Response Data below for field type specifications).

Card Set 7 (8A10). Description of the run is written on three cards.

Item Pool

LINDSCO and ADADSCO. To score the response data, a file containing the item pool item parameter estimates must be prepared beforehand and placed in a file called IPOOL. The file consists of a line for each item in the pool with the following information:

1. A *unique* item number;
2. Estimate of the *a* parameter;
3. Estimate of the *b* parameter;
4. Estimate of the *c* parameter;
5. Correct alternative for this item, i.e., the keyed response.

For LINDSCO, only Items 1 through 4 must be supplied; for ADADSCO, Item 5 must be supplied also, although it could be a "dummy" key (e.g., a blank), since the data may already be scored (see columns 44-45 for Card Set 1).

The exact format of this information is not critical, since it is read with a user-specified variable format. However, the following limitations must be observed: (1) the information must be read in the above order; (2) the item number must be read in integer mode; (3) the item parameter estimates must be read in floating point; and (4) the key, if ADADSCO is being used, must be read in integer mode.

A typical format for LINDSCO could be

(10X,I4,3F10.2) .

For ADADSCO, a typical format might be

(10X,I4,3F10.2,I2) .

All three parameter estimates must be read even if the user is using a one- or two-parameter model. This presents no difficulties, however, since in the case of, say, a two-parameter model, the third parameter is 0 for all items. This may be accomplished by reading blanks or zeros, or by editing item parameter estimates (see below).

The number of items in the pool may range from the number of items in the test, *M*, to 600. If the item pool for LINDSCO consists of only the items being scored in the test, then OPT2 should be set to 1. This indicates to the program that items do not have to be searched. On the other hand, if the pool consists of items in addition to those used in the present test, then OPT2 should be set to 0. This instructs the program to search for the item and to retrieve the corresponding item parameters. For both LINDSCO and ADADSCO, if at least one of the items being called for is not found in the pool, the program prints a message; and the unavailable item is treated as an omitted item.

Editing of item parameter estimates. LINDSCO and ADADSCO have several options to edit item parameter estimates. If OPT3=1, the program checks that the item parameter estimates are within certain bounds. For the discrimination (*a*) parameter, the program checks to see if the estimate exceeds AMAX; if it does, it is set to AMAX. For the difficulty (*b*) parameter, if the estimate is below BMIN, it is set to BMIN; if it is above BMAX, it is set to BMAX. For the "guessing" (*c*) parameter, the program checks to see if the estimate exceeds CMAX; if it does, it is set to CMAX. If the user wants to edit only one or two parameters, the limits of the other parameters should be chosen so that the editing has no effect.

A more radical form of editing is also possible. If OPT3=2, then in addition to the editing caused by OPT3=1, the program sets all c parameter estimates to CMAX. If CMAX=0.0, this implies that a two-parameter model is in effect. If OPT3=3, then in addition to the editing caused by OPT3=1 and OPT3=2, the program sets all a parameter estimates to AMAX.

LINPSCO. For polychotomous scoring, the item pool consists of the following information for graded normal and logistic ogive models:

1. A *unique* item identification number;
2. The "discrimination" parameter, which is common to all response categories;
3. m_g-1 "difficulty" parameters, where m_g is the number of response categories in the g^{th} item. Since m_g can be at most 10, there would be at most 9 difficulty parameters.

The exact format for reading this information is not crucial, since it is read by a user-supplied format statement. However, the following restrictions must be observed: (1) the identification number is read first, in integer mode; (2) next, the estimated discrimination parameter is read in floating point mode; (3) the m_g-1 "difficulty" parameters are read next, with the difficulty of the best alternative followed by the second best alternative, and so forth.

Since the program allows the number of categories to differ from item to item, the format should be specified so that it can read the information for the item with the most response categories. For example, if in a given test, the maximum number of response categories is seven, then there should be at most six difficulty parameters. The format for such pools might be as follows:

(I4,6X,F5.2/10X,6F5.2) .

In this format the item identification number is read in the I4 field; the discrimination parameter is read next in format F5.2; and the six difficulty values are read from the next card, beginning in column 11.

For the nominal logistic model, the item information is read in the following order:

1. A *unique* item identification number;
2. m_g "slope" parameters; and
3. m_g intercept parameters.

Differing from the graded models, in the nominal model there is a pair of parameters (a slope and an intercept) associated with *each* response category. Since the response categories are not ordered in the nominal model, the order in which the parameters are read is unimportant. However, the ordinal position in which the parameters appear in the pool must correspond with the integer associated with that response category. As in the graded models, the format should be able to read the information for the item with most response categories. For example, if the maximum number of response categories is five, the format

could be

(I4,16X,5F5.2,5X,5F5.2) .

In this format, the item identification number is read in the I4 field; next, the five slope parameters are read in 5F5.2; and finally, the five intercept parameters are read in the last set of 5F5.2 fields.

Test Response Data

Data for all testees must be on a file called DATA. The structure of this file differs slightly for each of the programs. In all cases, however, the last record of DATA must be an end-of-record marker.

LINDSCO. This program requires that for each individual the following information be provided on DATA:

1. Name,
2. Identification number, and
3. Responses to the test items.

The exact format of this information is not critical, since it is read with a user-supplied variable format; but the information must appear in the above order. Two words are used for testee name; thus, name should be read with two alphanumeric words, e.g., 2A10. This allows for up to 20 characters. The testee identification is read with an alphanumeric field of at least 1 column, e.g., A1, A9. Test item responses are read with an integer format, e.g., 20I1.

The test data may be raw item responses (i.e., the number of the alternatives chosen) or scored (i.e., 0 for incorrect and 1 for correct). However, in either case, a scoring key must be provided (see Card Set 5 for LINDSCO). The key will contain the number of the correct alternative if raw data are read. If the data are already scored, a "dummy" key full of "1's" must be provided.

Omitted items are indicated by the integer IOMIT (see columns 46 and 47 of Card Set 1 for LINDSCO). For raw data, this will normally be an integer greater than the number of alternatives. Similarly, for scored (0-1) data IOMIT must be an integer greater than 1.

ADADSCO. The program requires that the following information be provided on DATA for each individual:

1. Name,
2. Identification number,
3. Number of items answered by the testee (i.e., number of items attempted),
4. Item identification numbers of items attempted, and
5. Responses to the test items.

This information is read in the above order with a user-supplied variable format; thus, the exact format is not critical. However, the following limitations must be observed. Even though the number of items administered usually varies across individuals in an adaptive test, this program assumes that the data record for each testee is formally the same (i.e., that there is the same number of data

lines per testee and that these lines contain similar information). Thus, if the maximum number of items taken by anyone is MMAX (see Card Set 1 for ADADSCO), but any particular testee takes *M* items, where *M*<MMAX, then that testee's record should be "padded" to MMAX items. This can be accomplished by leaving an appropriate number of blank fields. The name is dimensioned for two words so the format should allow for two words, e.g., 2A10. The identification number is read with an alphanumeric format, e.g., A8. The number of items is read in integer mode. The item identification numbers and item responses are also read in integer mode. Note that in reading the item identification numbers and the item responses, the format should read MMAX of each, even if some of these will be blank for a given individual.

As an example assume that MMAX was 25; then the variable format could be

(2A10,A10,I2/20I4/5I4/25I1).

In this format, the name, testee identification, and *M* are read from the first card; the item identification numbers are read from the next two cards; and finally, the item responses are read from the fourth card. Note that for testees attempting 20 items or less, the third card will be blank.

The item responses may be scored or raw data. For scored data, the responses have been reduced to three categories: correct, incorrect, and omitted. In this case, IFLAG should be set to the integer corresponding to the correct code, and IOMIT should be set to the code for omitted responses. Note that if IFLAG>0, the program ignores the key read as part of the item pool. For raw data, the key will have been read as part of the item pool; IFLAG must therefore be set to 0. IOMIT will still be operational, however; and it must be set to an integer other than the highest numbered response alternative.

LINPSCO. The DATA file is similar to LINDSCO's with the exception that the item responses must include the response category chosen by the testee for a given item. For graded models, the convention that the best response category be coded "1," second best "2," and so forth, must be obeyed. For the nominal logistic model, this convention does not apply; but care must be taken so that a category's response code matches the ordinal position of that category in the IPOOL file. For either graded or nominal data, the code for omitted responses should be an integer greater than the maximum number of response categories.

Output

Four kinds of output are produced by each program: program parameters, item parameters, computational messages, and testee data.

Program Parameters

The output consists of the information in Card Set 1, the description of the run, and the variable formats for reading the item pool and the testee's raw data.

Item Parameters

LINDSCO and LINPSCO. The output consists of item identification number, scoring key, rejection key (i.e., whether or not the item was included in the computations), and the item parameter estimates. If the estimates have been

edited, the edited values will be printed. An option (see column 10 of Card Set 1) permits all of this information to be punched as well. If subscale scoring has been requested, the item identification number of the items in each subscale will be printed.

ADADSCO. The user has the option, but only for the first 10 testees, to print the following: testee's name and identification number; and for each item attempted, the item identification number, the response to that item, and the item parameter estimates.

Computational Messages

The program will print a testee's name and identification number if (1) a response pattern is found with all items correct or incorrect, excluding omitted or rejected items; (2) a zero score has been obtained; or (3) it was not possible to achieve convergence in scoring the testee's responses. For polychotomous data, a perfect or zero vector occurs if the testee responds with the best or worst response categories in all attempted items, exclusive of omitted or rejected items. If an item is not found in the pool or has extreme parameter estimates, an informative message is printed.

The number of testees read and the number of convergence failures are also printed. If Bayesian scoring has been requested, the number of nonconvergent cases will be zero.

Testee Data

LINDSCO. For each testee, the following information is written on a file called TAPE3:

1. Name;
2. Testee identification number;
3. Scale number, or in the case of total score, a "T";
4. Proportion of items answered correctly;
5. Maximum likelihood or Bayesian estimate of θ;
6. The response pattern information for maximum likelihood scoring or the posterior variance of θ for Bayesian scoring;
7. The number of items used in the estimation of θ, excluding items rejected, omitted, or not found;
8. The test information associated with the estimated θ (for Bayesian scoring, the information is computed using the normal ogive model);
9. The true score corresponding to the estimated θ;
10. For maximum likelihood scoring,
    a. The number of Newton-Raphson iterations needed to achieve convergence and
    b. The standard error of θ.

The format used for writing this information for total scores is (X,2A10,A9,*T*,F5.2,2F7.2,I4,2F7.2,I4,F7.2) .

The subscale results are written with (X,2A10,A9,I2,F5.2,2F7.2,I4,2F7.2,I4,F7.2) .

ADADSCO. The same information is written as that for LINDSCO with the exception of the scale number. The format is
(X,2A10,A9,F5.2,2F7.2,I4,2F7.2,I4,F7.2) .

LINPSCO. For LINPSCO, the following information is written:

1. Name;
2. Testee identification number;
3. Proportion of "best" responses;
4. Maximum likelihood estimate of θ;
5. The response pattern information;
6. The number of items used in the estimation of θ excluding items rejected, omitted, or not found;
7. The number of iterations needed to achieve convergence.
8. The test information associated with the estimated θ;
9. Estimated standard error of measurement.

AVAILABILITY

FORTRAN source code listings of the three programs are in Appendix C (LINDSCO), Appendix D (ADADSCO), and Appendix E (LINPSCO). Copies of the FORTRAN source code are available on cards or tape at nominal cost from

Psychometric Methods Program
Department of Psychology
University of Minnesota
75 East River Road
Minneapolis, Minnesota 55455

Telephone: 612-376-7378

Potential users of these programs should note that the programs were written for Control Data Corporation CYBER series computers. Because of the large word size of the CYBER computers, accurate computation on other computers may require the use of double-precision arithmetic. Minimal additional modifications required may include (1) modification of A10 fields to smaller sizes used by other computers and (2) modification of FORTRAN statements unique to the CYBER series computers.

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Appendix A

Item Parameter Estimation Programs

Program Name	Model	Reference
LOGIST	Three-parameter logistic ogive	Wood, R. L., Wingersky, M. S., & Lord, F. M. LOGIST: A computer program for estimating examinee ability and item characteristic curve parameters (Research Memorandum 76-6). Princeton, NJ: Educational Testing Service, 1976.
NORMOG	Three-parameter normal ogive	Kolakowski, D., Bock, R. A. A FORTRAN IV program for maximum likelihood item analysis and test scoring: Normal ogive model (Research Memo No. 12). Chicago: University of Chicago, Department of Education, Statistics Laboratory, 1970.
ESTEM	Three-parameter logistic *or normal ogive*	No program documentation available. For a description of the procedure see Urry, V. W., Ancillary estimators for the parameters of mental test models. Washington, DC: U.S. Civil Service Commission, Personnel Research and Development Center, 1974.
BICAL	One-parameter logistic ogive	Wright, B. D., & Mead, R. J. CALFIT: Sample-free item calibration with a Rasch measurement model (Research Memorandum No. 18). Chicago: University of Chicago, Department of Education, Statistical Laboratory, 1976.
LOGOG	Graded normal and logistic ogive, nominal logistic	Kolakowski, D., & Bock, R. D. LOGOG: A FORTRAN IV program for maximum likelihood item analysis and test scoring: Logistic model for multiple response (Research Memorandum No. 13). Chicago: University of Chicago, Department of Education, Statistical Laboratory, 1972.

Appendix B:

Examples of Program Use

The following examples serve to illustrate the use of each of the three programs. These results should also be useful in testing the accuracy of the results of the programs in different installations.

LINDSCO

The IPOOL file for these examples was

1	1.000	-2.000	.25
2	1.500	-1.000	.25
3	1.000	0.000	.25
4	1.500	1.000	.25
5	1.000	2.000	.25

The DATA file is also shown below. The first field contains the names; the second, the subject identification; and the third, the response patterns.

Name	I.D.	Responses
A00	1	00000
A01	2	00001
A02	3	00010
A03	4	00011
A04	5	00100
A05	6	00101
A06	7	00110
A07	8	00111
A08	9	01000
A09	10	01001
A10	11	01010
A11	12	01011
A12	13	01100
A13	14	01101
A14	15	01110
A15	16	01111
A16	17	10000
A17	18	10001
A18	19	10010
A19	20	10011
A20	21	10100
A21	22	10101
A22	23	10110
A23	24	10111
A24	25	11000
A25	26	11001
A26	27	11010
A27	28	11011
A28	29	11100
A29	30	11101
A30	31	11110
A31	32	11111

Example 1. This example illustrates the use of the normal ogive model (OPT4=1) for a five-item test (m=5) with a pool containing five items (INUP=5). The example also illustrates the use of parameter editing (OPT3=1) in which BMAX=BMIN=0.0, which in effect sets all b parameter estimates to 0.0. AMAX=2.00, which means that if there were a parameter estimates greater than 2, they would be set to 2.00. CMAX=.10, which means that any c parameter estimates greater than .10 will be edited to .10. This example also illustrates the use of subscales. The program parameter cards for this example were

```
  5    5  111 0.00 1.00 2.00 0.00 0.00  .10  4444
 (9X,I1,3F10.3)
    1    2    3    4    5
 00000
 11111
 (2A4,A2,10X,5I1)
 RUNS BASED ON ALL POSSIBLE RESPONSE VECTORS FOR A FIVE ITEM TEST


    1
    3    1
    2    3    5
```

The output corresponding to this example is shown on the following pages.

```
* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *

                                    LINDSCO
                                    -------

              LINEAR DICHOTOMUS SCORING WITH THREE PARAMETER MODELS


                              PSYCHOMETRIC METHODS PROGRAM
                              DEPARTMENT OF PSYCHOLOGY
                              UNIVERSITY OF MINNESOTA
                              MPLS. MINN. 55455


              INUP   =     5
              MMAX   =     5
              IOMIT  =  4444
              OPT1   =    -0
              OPT2   =     1
              OPT3   =     1
              OPT4   =     1
              TS     =     0
              TSS    =  1.00
              AMAX   =  2.00
              BMAX   =     0
              BMIN   =     0
              CMAX   =   .10
              VARIABLE FORMAT FOR POOL=(9X,I1,3F10.3)
              VARIABLE FORMAT FOR DATA=(2A4,A2,10X,5I1)
              RUNS BASED ON ALL POSSIBLE RESPONSE VECTORS FOR A FIVE ITEM TEST



                              ITEMS IN SUBSCALE NO=  1
  2     3     5

* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *

* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
                    ITEM ID S  KEYS  REJECTIONS    A         B         C

                        1        1       0       1.00        0        .10
                        2        1       0       1.50        0        .10
                        3        1       0       1.00        0        .10
                        4        1       0       1.50        0        .10
                        5        1       0       1.00        0        .10

* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *

      SUBJECT =A00           ID = 1       HAS NO  ANSWERS CORRECT IN TOTAL SCALE
      SUBJECT =A00           ID = 1       HAS NO  ANSWERS CORRECT IN SUBSCALE     1
      SUBJECT =A02           ID = 3       HAS NO  ANSWERS CORRECT IN SUBSCALE     1
      SUBJECT =A13           ID =14       HAS ALL ANSWERS CORRECT IN SUBSCALE     1
      SUBJECT =A15           ID =16       HAS ALL ANSWERS CORRECT IN SUBSCALE     1
      SUBJECT =A16           ID =17       HAS NO  ANSWERS CORRECT IN SUBSCALE     1
      SUBJECT =A18           ID =19       HAS NO  ANSWERS CORRECT IN SUBSCALE     1
      SUBJECT =A29           ID =30       HAS ALL ANSWERS CORRECT IN SUBSCALE     1
      SUBJECT =A31           ID =32       HAS ALL ANSWERS CORRECT IN TOTAL SCALE
      SUBJECT =A31           ID =32       HAS ALL ANSWERS CORRECT IN SUBSCALE     1

      CASES READ=   32 CASES NOT  CONVERGED=    0
```

Contents of TAPE3:

Testee Name	Testee Identification Number	Subscale: T=Total; 1=Scale 1	Proportion Correct	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items	Test Information Associated with $\hat{\theta}$	Expected Proportion Correct	Number of Iterations	Estimated Standard Error of Measurement
A00	1	T	0	-10.00	0	5	0	0	0	
A00	1	1	0	-10.00	0	5	0	0	0	
A01	2	T	.20	-1.06	1.48	5	1.07	.20	2	.82
A01	2	1	.33	-.65	1.51	3	1.36	.30	3	.81
A02	3	T	.20	-.95	.58	5	1.36	.22	5	1.31
A02	3	1	0	-10.00	0	5	0	0	0	
A03	4	T	.40	-.31	3.35	5	3.40	.42	3	.55
A03	4	1	.33	-.65	1.51	3	1.36	.30	3	.81
A04	5	T	.20	-1.06	1.48	5	1.07	.20	2	.82
A04	5	1	.33	-.65	1.51	3	1.36	.30	3	.81
A05	6	T	.40	-.50	3.08	5	2.84	.35	2	.57
A05	6	1	.67	.05	2.33	3	2.23	.57	2	.66
A06	7	T	.40	-.31	3.35	5	3.40	.42	3	.55
A06	7	1	.33	-.65	1.51	3	1.36	.30	3	.81
A07	8	T	.60	.07	3.98	5	3.94	.58	2	.50
A07	8	1	.67	.05	2.33	3	2.23	.57	2	.66
A08	9	T	.20	-.95	.58	5	1.36	.22	5	1.31
A08	9	1	.33	-.30	1.83	3	1.95	.43	3	.74
A09	10	T	.40	-.31	3.35	5	3.40	.42	3	.55
A09	10	1	.67	.40	2.03	3	2.11	.71	2	.70
A10	11	T	.40	-.12	3.63	5	3.78	.50	2	.52
A10	11	1	.33	-.30	1.83	3	1.95	.43	3	.74
A11	12	T	.60	.27	3.71	5	3.88	.67	2	.52
A11	12	1	.67	.40	2.03	3	2.11	.71	2	.70
A12	13	T	.40	-.31	3.35	5	3.40	.42	3	.55
A12	13	1	.67	.40	2.03	3	2.11	.71	2	.70
A13	14	T	.60	.07	3.98	5	3.94	.58	2	.50
A13	14	1	1.00	10.00	0	5	0	0	0	
A14	15	T	.60	.27	3.71	5	3.88	.67	2	.52
A14	15	1	.67	.40	2.03	3	2.11	.71	2	.70
A15	16	T	.80	.75	2.82	5	2.94	.83	2	.60
A15	16	1	1.00	10.00	0	5	0	0	0	
A16	17	T	.20	-1.06	1.48	5	1.07	.20	2	.82
A16	17	1	0	-10.00	0	5	0	0	0	
A17	18	T	.40	-.50	3.08	5	2.84	.35	2	.57
A17	18	1	.33	-.65	1.51	3	1.36	.30	3	.81
A18	19	T	.40	-.31	3.35	5	3.40	.42	3	.55
A18	19	1	0	-10.00	0	5	0	0	0	
A19	20	T	.60	.07	3.98	5	3.94	.58	2	.50
A19	20	1	.33	-.65	1.51	3	1.36	.30	3	.81
A20	21	T	.40	-.50	3.08	5	2.84	.35	2	.57
A20	21	1	.33	-.65	1.51	3	1.36	.30	3	.81
A21	22	T	.60	-.11	3.94	5	3.79	.50	2	.50
A21	22	1	.67	.05	2.33	3	2.23	.57	2	.66
A22	23	T	.60	.07	3.98	5	3.94	.58	2	.50
A22	23	1	.33	-.65	1.51	3	1.36	.30	3	.81
A23	24	T	.80	.46	3.82	5	3.62	.74	2	.51
A23	24	1	.67	.05	2.33	3	2.23	.57	2	.66
A24	25	T	.40	-.31	3.35	5	3.40	.42	3	.55
A24	25	1	.33	-.30	1.83	3	1.95	.43	3	.74
A25	26	T	.60	.07	3.98	5	3.94	.58	2	.50
A25	26	1	.67	.40	2.03	3	2.11	.71	2	.70
A26	27	T	.60	.27	3.71	5	3.88	.67	2	.52
A26	27	1	.33	-.30	1.83	3	1.95	.43	3	.74
A27	28	T	.80	.75	2.82	5	2.94	.83	2	.60
A27	28	1	.67	.40	2.03	3	2.11	.71	2	.70
A28	29	T	.60	.07	3.98	5	3.94	.58	2	.50
A28	29	1	.67	.40	2.03	3	2.11	.71	2	.70
A29	30	T	.80	.46	3.82	5	3.62	.74	2	.51
A29	30	1	1.00	10.00	0	5	0	0	0	
A30	31	T	.80	.75	2.82	5	2.94	.83	2	.60
A30	31	1	.67	.40	2.03	3	2.11	.71	2	.70
A31	32	T	1.00	10.00	0	5	0	0	0	
A31	32	1	1.00	10.00	0	5	0	0	0	

Example 2. This example is identical to Example 1 except that the Bayesian scoring routine was used (OPT4=3) instead of the maximum likelihood normal ogive. Only the scoring results are shown.

Testee Name	Testee Identification Number	Subscale: T=Total; 1=Scale 1	Proportion correct	Bayesian estimate of θ	Bayesian Posterior Variance	Number of Items	Test Information Associated with θ	Expected Proportion Correct		
A00	1	T	0	-1.23	.31	5	.71	.17	0	0
A00	1	1	0	-1.04	.39	3	.69	.21	0	0
A01	2	T	.20	-.88	.35	5	1.58	.24	0	0
A01	2	1	.33	-.55	.44	3	1.55	.34	0	0
A02	3	T	.20	-.83	.38	5	1.73	.25	0	0
A02	3	1	0	-1.04	.39	3	.69	.21	0	0
A03	4	T	.40	-.34	.41	5	3.33	.41	0	0
A03	4	1	.33	-.55	.44	3	1.55	.34	0	0
A04	5	T	.20	-.89	.30	5	1.56	.23	0	0
A04	5	1	.33	-.55	.41	3	1.54	.33	0	0
A05	6	T	.40	-.51	.32	5	2.83	.35	0	0
A05	6	1	.67	.02	.44	3	2.22	.56	0	0
A06	7	T	.40	-.37	.33	5	3.23	.40	0	0
A06	7	1	.33	-.55	.41	3	1.54	.33	0	0
A07	8	T	.60	.11	.35	5	3.95	.60	0	0
A07	8	1	.67	.02	.44	3	2.22	.56	0	0
A08	9	T	.20	-.76	.28	5	1.92	.26	0	0
A08	9	1	.33	-.36	.39	3	1.87	.41	0	0
A09	10	T	.40	-.40	.30	5	3.14	.38	0	0
A09	10	1	.67	.23	.43	3	2.22	.65	0	0
A10	11	T	.40	-.25	.30	5	3.53	.44	0	0
A10	11	1	.33	-.36	.39	3	1.87	.41	0	0
A11	12	T	.60	.20	.33	5	3.93	.64	0	0
A11	12	1	.67	.23	.43	3	2.22	.65	0	0
A12	13	T	.40	-.40	.27	5	3.15	.38	0	0
A12	13	1	.67	.22	.42	3	2.22	.64	0	0
A13	14	T	.60	-.02	.28	5	3.89	.54	0	0
A13	14	1	1.00	.98	.50	3	1.35	.88	0	0
A14	15	T	.60	.19	.30	5	3.93	.63	0	0
A14	15	1	.67	.22	.42	3	2.22	.64	0	0
A15	16	T	.80	.69	.33	5	3.10	.81	0	0
A15	16	1	1.00	.96	.50	3	1.35	.88	0	0
A16	17	T	.20	-.82	.25	5	1.76	.25	0	0
A16	17	1	0	-1.04	.39	3	.69	.21	0	0
A17	18	T	.40	-.50	.26	5	2.84	.35	0	0
A17	18	1	.33	-.55	.44	3	1.55	.34	0	0
A18	19	T	.40	-.38	.27	5	3.19	.39	0	0
A18	19	1	0	-1.04	.39	3	.69	.21	0	0
A19	20	T	.60	.01	.29	5	3.91	.55	0	0
A19	20	1	.33	-.55	.44	3	1.55	.34	0	0
A20	21	T	.40	-.50	.24	5	2.84	.35	0	0
A20	21	1	.33	-.55	.41	3	1.54	.33	0	0
A21	22	T	.60	-.17	.25	5	3.69	.48	0	0
A21	22	1	.67	.02	.44	3	2.22	.56	0	0
A22	23	T	.60	-.01	.26	5	3.90	.55	0	0
A22	23	1	.33	-.55	.41	3	1.54	.33	0	0
A23	24	T	.80	.39	.27	5	3.73	.71	0	0
A23	24	1	.67	.02	.44	3	2.22	.56	0	0
A24	25	T	.40	-.37	.24	5	3.23	.40	0	0
A24	25	1	.33	-.36	.39	3	1.87	.41	0	0
A25	26	T	.60	-.02	.25	5	3.89	.54	0	0
A25	26	1	.67	.23	.43	3	2.22	.65	0	0
A26	27	T	.60	.17	.27	5	3.94	.62	0	0
A26	27	1	.33	-.36	.39	3	1.87	.41	0	0
A27	28	T	.80	.61	.30	5	3.29	.79	0	0
A27	28	1	.67	.23	.43	3	2.22	.65	0	0
A28	29	T	.60	-.03	.24	5	3.88	.54	0	0
A28	29	1	.67	.22	.42	3	2.22	.64	0	0
A29	30	T	.80	.34	.26	5	3.80	.69	0	0
A29	30	1	1.00	.96	.50	3	1.35	.88	0	0
A30	31	T	.80	.59	.32	5	3.33	.78	0	0
A30	31	1	.67	.22	.42	3	2.22	.64	0	0
A31	32	T	1.00	1.20	.37	5	1.72	.92	0	0
A31	32	1	1.00	.98	.50	3	1.35	.88	0	0

Example 3. This example illustrates the use of the maximum likelihood logistic scoring routine (e.g., OPT4=2) without subscale scoring. Only the scoring results are shown.

Testee Name	Testee Identification Number	Subscale: T=Total; 1=Subscale 1	Proportion Correct	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items	Test Information Associated with $\hat{\theta}$	Expected Proportion Correct	Number of Iterations	Estimated Standard Error of Measurement
A00	1	T	0	-10.00	0	5	0	0	0	
A01	2	T	.20	-1.05	1.20	5	.90	.20	2	.91
A02	3	T	.20	-99.99	-99.99	5	-99.99	-99.99	99	-99.99
A03	4	T	.40	-.29	3.59	5	3.68	.42	3	.53
A04	5	T	.20	-1.05	1.20	5	.90	.20	2	.91
A05	6	T	.40	-.46	3.32	5	2.95	.35	1	.55
A06	7	T	.40	-.29	3.59	5	3.68	.42	3	.53
A07	8	T	.60	.07	4.49	5	4.46	.58	2	.47
A08	9	T	.20	-99.99	-99.99	5	-99.99	-99.99	99	-99.99
A09	10	T	.40	-.29	3.59	5	3.68	.42	3	.53
A10	11	T	.40	-.11	4.01	5	4.26	.50	2	.50
A11	12	T	.60	.25	4.22	5	4.26	.66	2	.49
A12	13	T	.40	-.29	3.59	5	3.68	.42	3	.53
A13	14	T	.60	.07	4.49	5	4.46	.58	2	.47
A14	15	T	.60	.25	4.22	5	4.26	.66	2	.49
A15	16	T	.80	.71	2.74	5	2.72	.83	2	.60
A16	17	T	.20	-1.05	1.20	5	.90	.20	2	.91
A17	18	T	.40	-.46	3.32	5	2.95	.35	1	.55
A18	19	T	.40	-.29	3.59	5	3.68	.42	3	.53
A19	20	T	.60	.07	4.49	5	4.46	.58	2	.47
A20	21	T	.40	-.46	3.32	5	2.95	.35	1	.55
A21	22	T	.60	-.10	4.53	5	4.28	.50	2	.47
A22	23	T	.60	.07	4.49	5	4.46	.58	2	.47
A23	24	T	.80	.45	3.70	5	3.70	.74	2	.52
A24	25	T	.40	-.29	3.59	5	3.68	.42	3	.53
A25	26	T	.60	.07	4.49	5	4.46	.58	2	.47
A26	27	T	.60	.25	4.22	5	4.26	.66	2	.49
A27	28	T	.80	.71	2.74	5	2.72	.83	2	.60
A28	29	T	.60	.07	4.49	5	4.46	.58	2	.47
A29	30	T	.80	.45	3.70	5	3.70	.74	2	.52
A30	31	T	.80	.71	2.74	5	2.72	.83	2	.60
A31	32	T	1.00	10.00	0	5	0	0	0	

ADADSCO

IPOOL for this example consisted of 10 items:

1	1.00	-2.00	.25 1
2	1.25	-1.50	.25 1
3	1.50	-1.00	.25 1
4	1.75	-0.50	.25 1
5	1.00	0.00	.25 1
6	1.25	0.50	.25 1
7	1.50	1.00	.25 1
8	1.75	1.50	.25 1
9	1.00	2.00	.25 1
10	1.25	2.50	.25 1

The data for the 16 subjects used in the example are shown below:

```
1  A    10
1011101110
 1 2 3 4 5 6 7 8 910
2  B    4
1010
 2 4 6 8
3  C    5
11111
 1 2 3 4 5
4  D    5
00000
 6 7 8 910
5  E    8
11000000
 1 2 3 5 6 7 8 9
6  F    2
10
 3 7
7  G    6
011111
 1 2 4 6 8 9
8  H    9
101010101
 1 2 3 4 5 6 7 8 9
9  I    7
1100110
 1 3 4 5 6 810
10 J    3
110
 4 8 9
```

```
11 K    8
10110110
 2 3 4 6 7 8 910
12 L    9
101111111
 1 2 3 4 5 7 8 910
13 M    5
01001
 1 3 5 7 9
14 N    6
000001
 4 5 6 7 8 9
15 P    7
1011110
 1 2 4 5 6 7 8
16 Q    6
011011
 2 4 5 7 810
```

The program control cards for this example were

```
   10  10 1012 0.00 1.00 2.00 0.00 0.00  .10 1 3
 (8X,I2,3F10.2,I2)
     0
 (A2,1X,2A2,I2,/10I1,/10I2)
 DESCRIPTION
```

In this example the maximum number of items attempted by anyone was 10 (MMAX=10). Although the code for omitted items was 3 (IOMIT=3), IFLAG=1, which means the key to each item was read from IPOOL; however, in this case it was 1 for all items. OPT1=1 means that item information for the first 10 subjects will be printed. Editing of item parameters was requested (OPT3=1). The scoring algorithm was maximum likelihood logistic.

The entire output for this example is shown on the following pages.

ADADSCO

ADAPTIVE DICHOTOMUS SCORING WITH THREE PARAMETER MODELS

PSYCHOMETRIC METHODS PROGRAM
DEPARTMENT OF PSYCHOLOGY
UNIVERSITY OF MINNESOTA
MPLS. MINN. 55455

```
INUP   =   10
MMAX   =   10
IOMIT  =    3
IFLAG  =    1
OPT1   =    1
OPT2   =    0
OPT3   =    1
OPT4   =    2
TS     =    0
TSS    = 1.00
AMAX   = 2.00
BMAX   =    0
BMIN   =    0
CMAX   =  .10
VARIABLE FORMAT FOR POOL=(8X,I2,3F10.2,I2)
VARIABLE FORMAT FOR DATA=(A2,1X,2A2,I2,/10I1,/10I2)
DESCRIPTION
```

Item Identification Number	Scored Answer	Testee Number	Discrimination Parameter (*a*)	Difficulty Parameter (*b*)	"Guessing" Parameter (*c*)
		1	A		
1	1		1.00	0	.10
2	0		1.25	0	.10
3	1		1.50	0	.10
4	1		1.75	0	.10
5	1		1.00	0	.10
6	0		1.25	0	.10
7	1		1.50	0	.10
8	1		1.75	0	.10
9	1		1.00	0	.10
10	0		1.25	0	.10
		2	B		
2	1		1.25	0	.10
4	0		1.75	0	.10
6	1		1.25	0	.10
8	0		1.75	0	.10
		3	C		
1	1		1.00	0	.10
2	1		1.25	0	.10
3	1		1.50	0	.10
4	1		1.75	0	.10
5	1		1.00	0	.10

SUBJECT C ID= 3 HAS ALL ANSWERS RIGHT

Item Identification Number	Scored Answer	Testee Number	Discrimination Parameter (*a*)	Difficulty Parameter (*b*)	"Guessing" Parameter (*c*)
		4	D		
6	0		1.25	0	.10
7	0		1.50	0	.10
8	0		1.75	0	.10
9	0		1.00	0	.10
10	0		1.25	0	.10

```
          SUBJECT D                    ID= 4        HAS NO RIGHT ANSWERS
        5          E
 1   1           1.00           0           .10
 2   1           1.25           0           .10
 3   0           1.50           0           .10
 5   0           1.00           0           .10
 6   0           1.25           0           .10
 7   0           1.50           0           .10
 8   0           1.75           0           .10
 9   0           1.00           0           .10
        6          F
 3   1           1.50           0           .10
 7   0           1.50           0           .10
        7          G
 1   0           1.00           0           .10
 2   1           1.25           0           .10
 4   1           1.75           0           .10
 6   1           1.25           0           .10
 8   1           1.75           0           .10
 9   1           1.00           0           .10
        8          H
 1   1           1.00           0           .10
 2   0           1.25           0           .10
 3   1           1.50           0           .10
 4   0           1.75           0           .10
 5   1           1.00           0           .10
 6   0           1.25           0           .10
 7   1           1.50           0           .10
 8   0           1.75           0           .10
 9   1           1.00           0           .10
        9          I
 1   1           1.00           0           .10
 3   1           1.50           0           .10
 4   0           1.75           0           .10
 5   0           1.00           0           .10
 6   1           1.25           0           .10
 8   1           1.75           0           .10
10   0           1.25           0           .10
       10          J
 4   1           1.75           0           .10
 8   1           1.75           0           .10
 9   0           1.00           0           .10
        CASES  READ=   16 CASES NOT  CONVERGED=     0
```

Testee Name	Testee Identification Number	Proportion Correct	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items	Test Information Associated with θ	Expected Proportion Correct	Number of Iterations	Estimated Standard Error of Measurement
A	1	.70	.34	9.65	10	9.65	.71	3	.32
B	2	.50	-.22	5.06	4	4.66	.43	2	.44
C	3	1.00	10.00	0	5	0	0	0	0
D	4	0	-10.00	0	5	0	0	0	0
E	5	.25	-.78	3.15	8	2.69	.24	1	.56
F	6	.50	-.09	2.57	2	2.57	.50	2	.62
G	7	.83	.79	3.13	6	3.12	.87	2	.57
H	8	.56	-.09	9.85	9	9.55	.50	2	.32
I	9	.57	.05	8.03	7	8.03	.58	2	.35
J	10	.67	.43	3.18	3	3.20	.77	2	.56
K	11	.63	.13	9.62	8	9.62	.62	2	.32
L	12	.89	.89	4.02	9	4.02	.89	3	.50
M	13	.40	-.29	3.59	5	3.68	.42	3	.53
N	14	.17	-1.08	1.40	6	.85	.18	2	.84
P	15	.71	.25	7.55	7	7.52	.68	2	.36
Q	16	.67	.23	7.03	6	7.03	.67	2	.38

LINPSCO

Following are sample runs from LINPSCO using graded models and the nominal logistic model.

Graded models. The IPOOL file for these examples was

```
1 1.5  3.0  2.0  4.5  3.0
2 1.5  2.0  1.0  3.0  1.5
3 1.5  1.0  0.0  1.5  0.0
4 1.5  0.0 -1.0  0.0 -1.5
5 1.5 -1.0 -2.0 -1.5 -3.0
6 1.5 -2.0 -3.0 -3.0 -4.5
```

The DATA file, including subject identification and item responses, was as follows. Note that in coding the item responses, a "1" indicated the "best" response and a "3" indicated the "poorest," as specified by the item difficulty parameters in IPOOL.

```
 1        333211
 2        332111
 3        321212
 4        112121
 5        112233
 6        222222
 7        122221
 8        322223
 9        111333
10        111222
11        333222
12        333111
13        222111
14        211111
```

The following is an example of the logistic graded model (OPT4=1) with a 1.7 scaling factor. In this example the *b* parameters for the items were taken from columns 3-4 of the IPOOL file. The option and format cards for this example were

```
    6    6201 1 1.70                                  4
(I1,1X,F3.1,2(1X,F4.1))
222222
    1     2     3     4     5     6
000000
(2A7,A1,6I1)
EXAMPLE RUN OF THE LOGISTIC GRADED MODEL--USES THE FIRST PAIR OF B
PARAMETERS FROM ITEM POOL
```

The output from this run was as follows:

```
                         LINPSCO
                         =======

        LINEAR POLYCHOTOMUS SCORING WITH TWO PARAMETER MODELS


                  PSYCHOMETRICS METHODS PROGRAM
                  DEPARTMENT OF PSYCHOLOGY
                  UNIVERSITY OF MINNESOTA
                  MPLS.  MINN. 55455


        INUP    =   6
        MMAX    =   6
        IOMIT   =   4
        OPT1    =   0
        OPT2    =   1
        OPT4    =   1
        MAXCAT  =   2
        D       = 1.7
        VARIABLE FORMAT FOR POOL =(I1,1X,F3.1,2(1X,F4.1))
        VARIABLE FORMAT FOR DATA =(2A7,A1,6I1)
        EXAMPLE RUN OF THE LOGISTIC GRADED MODEL--USES THE FIRST PAIR OF B
        PARAMETERS FROM ITEM POOL


ITEM ID =      1     REJECTION =  0
  A:    1.50
  B:    3.00  2.00

ITEM ID =      2     REJECTION =  0
  A:    1.50
  B:    2.00  1.00

ITEM ID =      3     REJECTION =  0
  A:    1.50
  B:    1.00     0

ITEM ID =      4     REJECTION =  0
  A:    1.50
  B:       0 -1.00

ITEM ID =      5     REJECTION =  0
  A:    1.50
  B:   -1.00 -2.00

ITEM ID =      6     REJECTION =  0
  A:    1.50
  B:   -2.00 -3.00


CASES READ =   14  CASES NOT CONVERGED =    0
```

Testee Identification	Proportion of "Best" Responses (Coded 1)	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items Used to Estimate θ	Number of Iterations	Test Information Associated with $\hat{\theta}$	Estimated Standard Error of Measurement
1	.33	-.50	4.72	6	2	4.25	.46
2	.50	.50	4.72	6	2	4.25	.46
3	.33	.35	3.69	6	3	4.28	.52
4	.67	1.52	2.63	6	3	4.11	.62
5	.33	-.00	4.21	6	3	4.41	.49
6	0	-.00	5.16	6	2	4.41	.44
7	.33	.51	4.88	6	2	4.25	.45
8	0	-.51	4.88	6	2	4.25	.45
9	.50	-.00	.96	6	3	4.41	1.02
10	.50	.52	2.65	6	2	4.25	.61
11	0	-1.51	4.86	6	2	4.11	.45
12	.50	-.00	4.20	6	3	4.41	.49
13	.50	1.51	4.86	6	2	4.11	.45
14	.83	2.69	3.12	6	2	2.67	.57

Following is an example of use of the normal ogive graded model (OPT4=2) using the same DATA and IPOOL as the previous example. In this example the *b* parameters for the items were taken from columns 5 and 6 of the IPOOL file. Input control cards for this example were

```
  6   0201 2                                    4
(I1,1X,F3.1,11X,F4.1,1X,F4.1)
222222
   1     2     3     4     5     6
000000
(2A7,A1,6I1)
EXAMPLE RUN OF THE NORMAL OGIVE GRADED MODEL--USES SECOND PAIR OF B
PARAMETERS FROM ITEM POOL
```

Output was as follows:

```
                         LINPSCO
                         ======

        LINEAR POLYCHOTOMUS SCORING WITH TWO PARAMETER MODELS

                         PSYCHOMETRICS METHODS PROGRAM
                         DEPARTMENT OF PSYCHOLOGY
                         UNIVERSITY OF MINNESOTA
                         MPLS.  MINN. 55455

        INUP    =   6
        MMAX    =   6
        IOMIT   =   4
        OPT1    =   0
        OPT2    =   1
        OPT4    =   2
        MAXCAT  =   2
        VARIABLE FORMAT FOR POOL =(I1,1X,F3.1,11X,F4.1,1X,F4.1)
        VARIABLE FORMAT FOR DATA=(2A7,A1,6I1)
        EXAMPLE RUN OF THE NORMAL OGIVE GRADED MODEL--USES SECOND PAIR OF B
        PARAMETERS FROM ITEM POOL

ITEM ID =       1      REJECTION =  0
  A:     1.50
  B:     4.50  3.00

ITEM ID =       2      REJECTION =  0
  A:     1.50
  B:     3.00  1.50

ITEM ID =       3      REJECTION =  0
  A:     1.50
  B:     1.50     0

ITEM ID =       4      REJECTION =  0
  A:     1.50
  B:        0 -1.50

ITEM ID =       5      REJECTION =  0
  A:     1.50
  B:    -1.50 -3.00

ITEM ID =       6      REJECTION =  0
  A:     1.50
  B:    -3.00 -4.50

CASES READ =   14  CASES NOT CONVERGED =    0
```

1	.33	-.75	2.97	6	2	3.36	.58
2	.50	.75	2.97	6	2	3.36	.58
3	.33	-.04	8.00	6	2	3.42	.35
4	.67	1.85	8.05	6	2	3.39	.35
5	.33	-.00	11.98	6	2	3.42	.29
6	0	-.00	11.58	6	2	3.42	.29
7	.33	1.09	9.50	6	2	3.39	.32
8	0	-1.09	9.50	6	2	3.39	.32
9	.50	-.00	12.80	6	1	3.42	.28
10	.50	.75	12.29	6	2	3.36	.29
11	0	-2.25	5.18	6	2	3.35	.44
12	.50	-.00	3.19	6	2	3.42	.56
13	.50	2.25	5.13	6	2	3.35	.44
14	.33	3.92	2.05	6	2	2.25	.70

Nominal logistic model. Following is an example of use of the nominal logistic model (OPT4=3). The DATA file was

```
10001 38 99464541341111224422111211114111141111121111111111
10002 381038345411144114141411441111141111114114111414111
10003 38 940005424141121114412141211114111144111111411111241
10005 381042450424222444424211142442421222421212121222241
10004 38 995434441414444414144444414111144411114114141144411
10005 381045285411144151214551121122111131111155555555551
10004 38103544544351111151411111441115111141141111111114111
10008 38 9933494232455143233143524155555555555555555555555
10009 3810534444142124152232134413124214124221114321222554
10010 3810515094444441114445111411111411414111111111111144141
10011 3810529454111111115114111111111111111111111111111111
10012 3810384924423231334333114222251313251122144511242151
10013 3810540444414444144111441444111441411441114241511111
10015 38 9524554144512132544414111111111212411344111112141
10014 38105983542112411421441444412112141211411141111154411
10015 3810512954211141112441111411111111111111111111111141
10014 3810595265244132113142111425121111114111141111131451
10018 3810524844114411141324111414114244431441114114115141
10019 3810528254414411144241112433113442411241121311114114
10020 25104114344444444141441114444441414444141114144144444
```

IPOOL was

3417	0.000000	0.000000	0.000000	0.000000
	0.000000	0.000000	0.000000	0.000000
3242	0.870169	0.165539	-1.212113	0.176405
	0.843205	0.266821	-2.110617	1.006591
3251	1.039257	0.007821	-1.157598	0.110520
	0.900771	-0.711543	-1.432918	1.237689
3204	0.870227	0.313705	-1.132723	-0.059209
	0.510097	-0.183194	-1.493435	1.106532
3422	0.649335	-0.056839	-0.936221	0.143745
	0.947914	-0.510533	-1.591918	1.154558
3411	0.997044	-0.057076	-1.040348	0.106380
	0.223949	-0.511724	-0.842978	1.130754
3421	0.903633	0.452403	-1.315750	-0.040285
	1.324394	0.196605	-2.289410	0.708330
3277	0.935577	0.125247	-1.013713	-0.047610
	1.754989	-0.277937	-1.882968	0.405916
3408	1.267512	0.165917	-1.188968	-0.244462
	0.722900	-0.503622	-1.456565	1.237267
3250	0.400782	0.236527	-0.675647	0.032338
	-0.105035	-0.081050	-0.762658	0.968744
3012	0.914806	-0.087146	-0.807633	-0.020027
	0.880125	-0.361430	-1.133896	0.615221
3010	0.000000	0.000000	0.000000	0.000000
	0.000000	0.000000	0.000000	0.000000
3405	1.213009	-0.160534	-1.049275	-0.005201
	0.703199	-0.472308	-1.271001	1.040191
3213	0.941547	0.120534	-1.210924	0.154792
	1.610184	-0.227101	-2.405601	1.014638
3207	1.190701	0.289311	-1.692915	0.204903
	2.322618	-0.227103	-3.302494	1.207041
3079	1.382173	-0.138215	-1.203993	-0.039965
	1.753215	-0.061800	-2.059020	0.968273
3002	1.160829	-0.009732	-1.500254	0.349206
	0.157054	-0.506044	-1.636365	1.987376
3039	1.234116	-0.075624	-0.934679	-0.223813
	1.111208	0.012123	-1.527765	0.404369
3279	1.020419	0.034131	-0.950948	-0.106622
	0.353335	-0.287433	-1.247386	0.981456
3262	1.603121	-0.068531	-1.228285	-0.303305
	2.697426	-0.693601	-2.469919	0.460094
3220	1.391045	-0.042953	-1.013781	-0.334310
	1.683738	-0.088790	-1.734153	0.139205
3208	1.022427	0.183645	-1.046231	-0.159844
	1.574865	-0.443101	-1.656987	0.525223
3404	0.994791	-0.067707	-1.062704	0.135620
	1.010467	-0.657834	-1.145258	0.766626
3430	1.242329	0.078533	-1.435152	0.114271
	2.364325	-0.659730	-2.638202	1.133657
3006	1.121352	0.184404	-0.962735	-0.343020
	1.620360	-0.262232	-1.632686	0.274608
3237	1.352141	0.216193	-1.205470	-0.366864
	2.263497	-0.343737	-2.311491	0.359781
3022	0.603197	0.002103	-0.812300	0.007000
	0.973607	-0.472746	-1.024659	0.523197
3021	2.042249	0.393252	-1.696127	-0.737373
	3.702431	0.132937	-3.787033	-0.054436
3221	1.377861	0.131895	-1.134625	-0.373132
	2.120620	0.251772	-2.499555	0.094757
3017	1.543139	0.286432	-2.081177	0.249606
	2.042910	0.001304	-3.331305	1.267061
3246	1.564642	-0.007945	-1.298770	-0.257927
	2.293293	0.021343	-2.644136	0.326495
3076	1.283965	0.227021	-0.889192	-0.623795
	3.019197	-0.447594	-2.181694	-0.339909
3215	1.054357	-0.069429	-0.669305	-0.295623
	1.629671	-0.30951	-1.288305	-0.033315
3036	1.453187	0.284191	-1.620217	-0.102162
	1.771329	-0.348503	-2.527377	1.104548
3226	1.119323	-0.003934	-0.823243	-0.292120
	1.279163	-0.303697	-1.057345	0.081860
3239	1.330099	0.036376	-1.773188	0.406713
	2.393186	-0.114603	-3.584809	1.336283
3023	1.480476	-0.073318	-0.823643	-0.589715
	2.230098	-0.331496	-1.535212	-0.371390
3236	1.202460	-0.157735	-0.924427	-0.120298
	1.774003	-0.242500	-1.844767	0.313329
3028	1.060538	-0.131202	-0.860250	-0.069056
	1.633196	-0.843935	-1.242548	0.453307
3024	1.320054	0.287821	-1.559475	0.243501
	1.604725	0.560963	-3.220217	0.994529
3077	1.600690	-0.074231	-1.264068	-0.268341
	2.077034	-0.645201	-2.330619	0.904846
3029	0.691561	0.155307	-1.158516	0.311618
	1.310654	-1.378577	-1.585535	1.053456
3078	1.091246	0.129610	-1.359014	-0.460943
	3.629455	-0.593270	-3.131633	0.095448

Input control cards were

```
  43  22300 3                                         5
(I4,4(1X,F9.6),/,4X,4(1X,F9.6))
3333333333333333333333333333333333333333333333333333333
 3417 3251 3422 3421 3277 3408 3010 3405 3213 3079 3002 3220 3404 3430 3021 3221
 3076 3236 3029 3078 3239 3023
1000001000000000000000
(2A7,A1,43I1)
EXAMPLE RUN OF THE NOMINAL LOGISTIC MODEL
```

And the output from this run was

```
                              LINPSCO
                              ======


  LINEAR POLYCHOTOMUS SCORING WITH TWO PARAMETER MODELS


                   PSYCHOMETRICS METHODS PROGRAM
                   DEPARTMENT OF PSYCHOLOGY
                   UNIVERSITY OF MINNESOTA
                   MPLS.  MINN. 55455


  INUP    =  43
  MMAX    =  22
  IOMIT   =   5
  OPT1    =   0
  OPT2    =   0
  OPT4    =   3
  MAXCAT  =   3
  VARIABLE FORMAT FOR POOL =(I4,4(1X,F9.6),/,4X,4(1X,F9.6))
  VARIABLE FORMAT FOR DATA=(2A7,A1,43I1)
  EXAMPLE RUN OF THE NOMINAL LOGISTIC MODEL
```

```
ITEM ID =      0      REJECTION =  1
  A:      0      0      0     0
  B:      0      0      0     0

ITEM ID =  3251       REJECTION =  0
  A:   1.04    .01 -1.16    .11
  B:    .91   -.71 -1.43   1.24

ITEM ID =  3422       REJECTION =  0
  A:    .85   -.06  -.94    .14
  B:    .95   -.51 -1.59   1.15

ITEM ID =  3421       REJECTION =  0
  A:    .90    .45 -1.32   -.04
  B:   1.32    .20 -2.29    .77

ITEM ID =  3217       REJECTION =  0
  A:    .94    .13 -1.01   -.05
  B:   1.75   -.28 -1.88    .41

ITEM ID =  3408       REJECTION =  0
  A:   1.27    .17 -1.19   -.24
  B:    .72   -.50 -1.46   1.24

ITEM ID =      0      REJECTION =  1
  A:      0      0      0     0
  B:      0      0      0     0

ITEM ID =  3405       REJECTION =  0
  A:   1.22   -.16 -1.05   -.01
  B:    .70   -.47 -1.27   1.04

ITEM ID =  3213       REJECTION =  0
  A:    .94    .12 -1.22    .15
  B:   1.62   -.23 -2.41   1.01

ITEM ID =  3079       REJECTION =  0
  A:   1.38   -.14 -1.20   -.04
  B:   1.75   -.66 -2.06    .97

ITEM ID =  3002       REJECTION =  0
  A:   1.16   -.01 -1.50    .35
  B:    .16   -.51 -1.64   1.99

ITEM ID =  3220       REJECTION =  0
  A:   1.39   -.04 -1.01   -.33
  B:   1.68   -.09 -1.73    .14

ITEM ID =  3404       REJECTION =  0
  A:    .99   -.07 -1.06    .14
  B:   1.02   -.66 -1.15    .79

ITEM ID =  3400       REJECTION =  0
  A:   1.24    .08 -1.44    .11
  B:   2.36   -.86 -2.64   1.13

ITEM ID =  3021       REJECTION =  0
  A:   2.04    .39 -1.70   -.74
  B:   3.71    .13 -3.79   -.05

ITEM ID =  3221       REJECTION =  0
  A:   1.38    .13 -1.13   -.38
  B:   2.12    .28 -2.50    .09

ITEM ID =  3076       REJECTION =  0
  A:   1.29    .23  -.89   -.62
  B:   3.02   -.45 -2.18   -.39

ITEM ID =  3226       REJECTION =  0
  A:   1.20   -.16  -.92   -.12
  B:   1.77   -.24 -1.84    .31

ITEM ID =  3029       REJECTION =  0
  A:    .69    .16 -1.16    .31
  B:   1.31  -1.38 -1.59   1.65

ITEM ID =  3078       REJECTION =  0
  A:   1.69    .13 -1.36   -.46
  B:   3.63   -.59 -3.13    .10

ITEM ID =  3229       REJECTION =  0
  A:   1.33    .04 -1.77    .41
  B:   2.39   -.11 -3.58   1.31

ITEM ID =  3023       REJECTION =  0
  A:   1.49   -.07  -.82   -.59
  B:   2.24   -.33 -1.54   -.37

CASES READ =   20  CASES NOT CONVERGED =    0
```

Testee Identification		Proportion of "Best" Responses	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items Used to Estimate θ	Number of Iterations	Test Information Associated with $\hat{\theta}$	Estimated Standard Error of Measurement
8 99484	5	.50	-.63	9.16	20	3	9.12	.33
8103834	5	.65	-.02	6.24	20	3	6.21	.40
8 94000	5	.55	-.33	7.94	20	2	7.60	.35
8104245	0	.15	-1.31	12.19	20	2	12.11	.29
8 99543	4	.35	-1.10	11.43	20	2	11.44	.30
8104528	5	.59	-.47	7.11	17	2	7.11	.37
8105544	5	.71	-.07	5.17	17	3	5.16	.44
8 99334	9	.19	-1.73	9.55	16	2	9.55	.32
8105344	4	.32	-1.40	11.89	19	2	11.89	.29
8105150	9	.47	-.69	9.02	19	3	9.00	.33
8105294	5	.95	3.12	.59	19	3	.59	1.30
8103849	2	.16	-1.90	10.86	19	3	10.85	.30
8105404	4	.45	-.72	9.60	20	3	9.59	.32
8 95245	5	.56	-.51	7.98	18	3	7.97	.35
8105983	5	.40	-1.05	11.34	20	2	11.24	.30
8105129	5	.70	.00	6.17	20	3	6.14	.40
8105952	8	.47	-.85	10.09	19	3	10.09	.31
8105248	4	.55	-.49	8.39	20	3	8.39	.35
8105282	5	.40	-1.03	11.18	20	3	11.18	.30
5104114	3	.30	-.98	10.94	20	3	10.95	.30

```
      PROGRAM LINDSCO (INPUT,OUTPUT,DATA,IPOOL,TAPE1=DATA,TAPE2=IPOOL,TA
     1PE3,PUNCH)
      DIMENSION ITEM(600), A(600), B(600), C(600), INAD(300), KEY(300),
     1IREJ(300), IFORM(8), IRAW(300), INADS(300), IRESP(300), ISAD(60,25
     2), ADM(300), BDM(300), CDM(300), ISADS(300), DESC(24), NAME(2), IF
     3ORM1(8), NISS(25,2)
      INTEGER OPT1,OPT2,OPT3,OPT4
      REAL ITOT
      N=NC=0
************************************************************************
*                                                                      *
*READ OPTIONS AND PROGRAM PARAMETER FROM INPUT FILE DATA IS ON TAPE2    *
*                                                                      *
************************************************************************
      IPOOL=2
      READ 50, INUP,M,OPT1,OPT2,OPT3,OPT4,TS,TSS,AMAX,BMIN,BMAX,CMAX,IOM
     1IT
      READ 53, (IFORM1(I),I=1,8)
      READ (IPOOL,IFORM1) (ITEM(I),A(I),B(I),C(I),I=1,INUP)
************************************************************************
*                                                                      *
*                                                                      *
*START READING THE SPECIFIC DATA (SPECIFIC FOR THE RUN) FROM THE INPUT *
*INAD IS THE ITEM ID#S ADMINISTERED                                    *
*IREJ IS THE REJECTED ITEM ID S                                        *
*KEY  IS THE KEY FOR THE ITEMS IN INAD                                 *
*NSSC IS THE NUMBER OF SUBSCALES THAT WILL BE GIVEN TO THE PROGRAM     *
*NISS WILL HAVE THE NUMBER OF ITEMS IN EACH SUBSCALE TOGETHER WITH THE *
*NAME OF THE SUBSCALES                                                 *
*ISAD IS THE ITEM ID S IN EACH SUBSCALE                                *
*                                                                      *
*                                                                      *
************************************************************************
      READ 51, (INAD(I),I=1,M)
      READ 52, (IREJ(I),I=1,M)
      READ 52, (KEY(I),I=1,M)
      READ 53, (IFORM(I),I=1,8)
      READ 55, DESC
      PRINT 49
      PRINT 54, INUP,M,IOMIT,OPT1,OPT2,OPT3,OPT4,TS,TSS,AMAX,BMAX,BMIN,C
     1MAX,IFORM1,IFORM,DESC
C        THOSE ITEM ID S THAT ARE IN IREJ ARE SET TO ZERO ZERO ITEM ID S
C        WILL BE SKIPPED DURING THE COMPUTATIONS
      DO 1 I=1,M
1     IF (IREJ(I).EQ.1) INAD(I)=0
C     READ SUBSCALES
      READ 48, NSSC
      IF (NSSC.EQ.0) GO TO 5
      READ 56, (NISS(I,1),NISS(I,2),I=1,NSSC)
C     READ SSC INDEX
      DO 2 JJ=1,60
      DO 2 II=1,25
2     ISAD(JJ,II)=0
      DO 3 I=1,NSSC
      NI=NISS(I,1)
      READ 51, (ISAD(J,I),J=1,NI)
3     CONTINUE
      DO 4 II=1,NSSC
      NI=NISS(II,1)
      PRINT 58, II,(ISAD(JJ,II),JJ=1,NI)
4     CONTINUE
      PRINT 49
5     CONTINUE
      IF (OPT2.EQ.1) GO TO 9
************************************************************************
*                                                                      *
```

```
*                                                                       *
*IN THE NEXT DO LOOP THE ITEM PARAMETERS CORRESPONDING TO THE ITEMS     *
*IN INAD ARE RETRIVED FROM A,B,C, AND LOADED INTO ADM,BDM,CDM RESP.     *
*THE ENTRIES IN THE ADM,BDM,CDM ARE ZEROED FOR THE CASE OF ZERO ITEM    *
*ID IN THE INAD                                                         *
*                                                                       *
*                                                                       *
*************************************************************************
      DO 8 J=1,M
      IF (INAD(J).NE.0) GO TO 6
      ADM(J)=BDM(J)=CDM(J)=0
      GO TO 8
6     CONTINUE
      IFOUND=0
      DO 7 I=1,INUP
      IF (INAD(J).NE.ITEM(I)) GO TO 7
      IFOUND=1
      ADM(J)=A(I)
      BDM(J)=B(I)
      CDM(J)=C(I)
      GO TO 8
7     CONTINUE
      IF (IFOUND.EQ.0) INAD(J)=0
8     CONTINUE
      GO TO 11
C        THE NEXT SECTION IS USED IF OPTION 2 IS ON, IT WILL TAKE THE FI
C        PARAMETERS FROM THE POOL WITHOUT MAKING USE OF INAD
9     DO 10 I=1,M
      ADM(I)=A(I)
      BDM(I)=B(I)
      CDM(I)=C(I)
10    CONTINUE
C        IF OPTION 3 IS ON THE PARAMETERS A,B,C ARE CONSTRAINED WITHIN B
C        OF AMAX,AMIN,BMAX,BMIN,CMAX
11    IF (OPT3.EQ.0) GO TO 13
      DO 12 I=1,M
      IF (INAD(I).EQ.0) GO TO 12
      IF ((ADM(I).GT.AMAX).OR.(OPT3.EQ.3)) ADM(I)=AMAX
      IF (BDM(I).LT.BMIN) BDM(I)=BMIN
      IF (BDM(I).GT.BMAX) BDM(I)=BMAX
      IF ((CDM(I).GT.CMAX).OR.(OPT3.EQ.2)) CDM(I)=CMAX
12    CONTINUE
13    IF (OPT1.NE.1) GO TO 15
      DO 14 I=1,M
      PUNCH 57, INAD(I),KEY(I),IREJ(I),ADM(I),BDM(I),CDM(I)
14    CONTINUE
15    PRINT 57, (INAD(I),KEY(I),IREJ(I),ADM(I),BDM(I),CDM(I),I=1,M)
      PRINT 49
*************************************************************************
*                                                                       *
*                                                                       *
*READ A SUBJECT FROM TAPE1 CALCULATE THETA, LOOP BACK TO 5 ETC.         *
*                                                                       *
*                                                                       *
*************************************************************************
16    READ (1,IFORM) NAME,ID,(IRAW(I),I=1,M)
      DO 17 JJ=1,M
17    IRESP(JJ)=0
      IO=UNIT(1)
C     CHECK THE  END OF FILE ON DATA FILE
      IF (IO.LE.0) GO TO 18
      PRINT 59, IO
18    IF (IO.EQ.0) GO TO 47
      N=N+1
      ITOT=0.0
C        SET THE ITEM ID TO ZERO FOR THE OMMISSIONS (THAT IS READ IN FRO
```

```
C
C       AND SET THE RESPONSE VECTOR TO 1 IF THE ANSWER IS CORRECT
C
        DO 21 I=1,M
        INADS(I)=INAD(I)
        IF (IRAW(I).EQ.IOMIT) 19,20
19      INADS(I)=0
        GO TO 21
20      IF ((IRAW(I).EQ.KEY(I)).AND.(IREJ(I).EQ.0)) IRESP(I)=1
        ITOT=ITOT+FLOAT(IRESP(I))
21      CONTINUE
        ITINADS=0
        DO 22 KK=1,M
22      IF (INADS(KK).EQ.0) ITINADS=ITINADS+1
        KL=M-ITINADS
        ITOT=ITOT/FLOAT((KL))
        IF (ITOT.EQ.0.) 23,24
23      PRINT 60, NAME,ID
        IF (OPT4.EQ.3) GO TO 26
        T=-10.0
        SFORM=0.0
        TINFO=0.0
        IKL=KL
        ITER=0
        EXPTOT=0.0
        WRITE (3,63) NAME,ID,ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER
        GO TO 32
24      IF (ITOT.EQ.1.) 25,26
25      PRINT 61, NAME,ID
        IF (OPT4.EQ.3) GO TO 26
        T=10.0
        SFORM=0.0
        TINFO=0.0
        IKL=KL
        ITER=0
        EXPTOT=0.0
        WRITE (3,63) NAME,ID,ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER
        GO TO 32
*****************************************************************
*                                                               *
*                                                               *
*       NOW THE DATA IS READY TO MAKE THE CALLS TO THE APPROPRIATE ROUTINE
*TO ESTIMATE THE THETA.OPTION 4 WILL DETERMINE THE METHOD BY WHICH  *
*THE THETA ESTIMATE WILL BE FOUND                               *
*                                                               *
*                                                               *
*****************************************************************
26      IKL=KL
        IF (OPT4-2) 27,28,29
27      CALL MAXLNO (IRESP,INADS,M,M,ADM,BDM,CDM,50,.005,T,SFORM,IFAIL,TIN
       1FO,EXPTOT,ITER,SEM)
        GO TO 30
28      CALL MAXLK (M,INADS,IRESP,M,ADM,BDM,CDM,50,.005,IFAIL,SFORM,T,TINF
       1O,EXPTOT,ITER,SEM)
        GO TO 30
29      T=TS
        SFORM=TSS
        SEM=0.0
        CALL BAYES (M,INADS,IRESP,M,ADM,BDM,CDM,T,SFORM,TINFO,EXPTOT,ITER)
        GO TO 31
30      CONTINUE
        IF (IFAIL.EQ.0) GO TO 31
        PRINT 62, NAME,ID
C        SFORM AND T ARE SET TO -99.99 IN MAXLK IF NOT CONV
        NC=NC+1
*****************************************************************
```

```
*                                                                   *
*WRITE THE SUCCESFUL RESULTS TOTHE FILE TAPE3                       *
*                                                                   *
*********************************************************************
31    WRITE (3,63) NAME,ID,ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER,SEM
C        IF THERE IS NO SUBSCALE CALCULATIONS LOOP BACK TO READ A SUBJEC
C        OTHERWISE CONTINUE WTTH THE COMPUTATIONS FOR SUBSCALES
32    IF (NSSC.EQ.0) GO TO 16
      DO 46 I=1,NSSC
      NI=NISS(I,1)
      ITOT=0.0
      DO 35 J=1,M
      ISADS(J)=INADS(J)
      DO 34 K=1,NI
      IF (ISAD(K,I)-INADS(J)) 34,33,34
33    ITOT=ITOT+FLOAT(IRESP(J))
      GO TO 35
34    CONTINUE
      ISADS(J)=0
35    CONTINUE
      ITISADS=0
      DO 36 KK=1,M
36    IF (ISADS(KK).NE.0) ITISADS=ITISADS+1
      KL=ITISADS
      ITOT=ITOT/FLOAT(KL)
      IF (ITOT.EQ.0.0) 37,38
37    PRINT 66, NAME,ID,NISS(I,2)
      IF (OPT4.EQ.3) GO TO 40
      T=-10.00
      TINFO=EXPTOT=0.0
      ITER=0
      SFORM=0.0
      WRITE (3,64) NAME,ID,NISS(I,2),ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER
      GO TO 46
38    IF (ITOT.EQ.1.0) 39,40
39    PRINT 67, NAME,ID,NISS(I,2)
      IF (OPT4.EQ.3) GO TO 40
      T=10.0
      TINFO=EXPTOT=0.0
      ITER=0
      SFORM=0.0
      WRITE (3,64) NAME,ID,NISS(I,2),ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER
      GO TO 46
40    IKL=KL
      IF (OPT4-2) 41,42,43
41    CALL MAXLNO (IRESP,ISADS,M,M,ADM,BDM,CDM,50,.01,T,SFORM,IFAIL,TINF
     1O,EXPTOT,ITER,SEM)
      GO TO 44
42    CALL MAXLK (M,ISADS,IRESP,M,ADM,BDM,CDM,50,.01,IFAIL,SFORM,T,TINFO
     1,EXPTOT,ITER,SEM)
      GO TO 44
43    T=TS
      SFORM=TSS
      SEM=0.0
      CALL BAYES (M,ISADS,IRESP,M,ADM,BDM,CDM,T,SFORM,TINFO,EXPTOT,ITER)
      GO TO 45
44    IF (IFAIL.EQ.0) GO TO 45
      PRINT 68, NAME,ID,NISS(I,2)
45    WRITE (3,64) NAME,ID,NISS(I,2),ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER,
     1SEM
46    CONTINUE
      GO TO 16
47    PRINT 65, N,NC
      STOP
C
C
```

```
C
48    FORMAT (I5)
49    FORMAT (1H1)
50    FORMAT (2I4,X,4I1,6F5.2,2X,I2)
51    FORMAT (16I5)
52    FORMAT (80I1)
53    FORMAT (8A10)
54    FORMAT (T50,*LINDSCO*,/,T50*=======*,//////,T20,*LINEAR DICHOTOMUS
     1 SCORING WITH THREE PARAMETER MODELS*,////,T40*PSYCHOMETRIC METHOD
     2S PROGRAM*,/,T40*DEPARTMENT OF PSYCHOLOGY*,/,T40*UNIVERSITY OF MIN
     3NESOTA*,/,T40*MPLS. MINN. 55455*,/,///,T20*INUP*,T27*=*I5,/,T20,*M
     4MAX*,T27*=*I5,/,T20,*IOMIT*,T27*=*,I5,/,T20*OPT1*,T27*=*I5,/,T20*O
     5PT2*,T27*=*I5,/,T20*OPT3*,T27*=*I5,/,T20*OPT4*,T27*=*,I5,/,T20*TS*
     6,T27*=*F5.2,/,T20*TSS*,T27*=*F5.2,/,T20*AMAX*,T27*=*F5.2,/,T20,*BM
     7AX*,T27,*=*F5.2,/,T20*BMIN*,T27,*=*F5.2,/,T20*CMAX*,T27,*=*F5.2,/,
     8T20,*VARIABLE FORMAT FOR POOL=*8A10,/,T20,*VARIABLE FORMAT FOR DAT
     9A=*8A10,/,T20,8A10,/,T20,8A10,/,T20,8A10,/)
55    FORMAT (8A10)
56    FORMAT (2I5)
57    FORMAT (*1*,29X,*ITEM ID S*2X,*KEYS*2X,*REJECTIONS*,4X,*A*,9X,*B*,
     19X,*C*,/,60(/30X,I5,5X,I3,5X,I3,1X,F10.2,1X,F10.2,1X,F10.2))
58    FORMAT (///,40X,*ITEMS IN SUBSCALE NO=*I3,/,10(20I6,/))
59    FORMAT (10X,*PARITY ERROR ON TAPE*,90X,I2)
60    FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS  NO ANSWERS *,*CORRE
     1CT IN TOTAL SCALE*)
61    FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS ALL ANSWERS *,*CORRE
     1CT IN TOTAL SCALE*)
62    FORMAT (10X,*COMPUTATIONAL PROBLEMS WITH SUBJECT =*,2A10,* ID =*,A
     19,*  IN TOTAL TE*)
63    FORMAT (X,2A10,A9,* T*,F5.2,2F7.2,I4,2F7.2,I4,F7.2)
64    FORMAT (X,2A10,A9,I2,F5.2,2F7.2,I4,2F7.2,I4,F7.2)
65    FORMAT (/10X,*CASES  READ=*,I5,* CASES NOT  CONVERGED=*,I5)
66    FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS NO  ANSWERS *,*CORRE
     1CT IN SUBSCALE *,I5)
67    FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS ALL ANSWERS *,*CORRE
     1CT IN SUBSCALE *,I5)
68    FORMAT (10X,*MAXIMUM LIKELIHOOD ESTIMATION DOES NOT CONVERGE*,*FOR
     1 THE SUBJECT = *,2A10,* ID = *,A9,*  ON SUBSCALE *,I5)
      END
      SUBROUTINE BAYES (M,ITM,RESP,N,A,B,C,BTHET,BVAR,TINFO,EXPTOT,ITER)
      INTEGER RESP(M),ITM(M)
      REAL A(N),B(N),C(N)
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      CALL BSCOR (BTHET,BVAR,B(I),A(I),C(I),RESP(I))
1     CONTINUE
      CALL NOSTAT (M,ITM,A,B,C,BTHET,TINFO,EXPTOT)
      ITER=0
      RETURN
      END
      SUBROUTINE BSCOR (BTHET,BVAR,DIF,DIS,GUESP,IRESP)
      D=(DIF-BTHET)/SQRT(2.0*(1.0/DIS**2+BVAR))
      ERFD=ERFNP(D)
      EDSQ=EXP(D**2)
      IF (EDSQ.EQ.0.0) RETURN
      EDSQI=1.0/EDSQ
      XKINV=0.5*(1.0-ERFD)
      XLINV=GUESP+(1.0-GUESP)*XKINV
      IF ((XLINV.EQ.0.0).OR.(XKINV.EQ.0.0)) RETURN
      XL=1.0/XLINV
      IF (IRESP.NE.1) GO TO 1
      S=0.398942*(SQRT(BVAR)/SQRT(1.0+(1.0/DIS**2)/BVAR))*(1.0/XKINV)*ED
     1SQI
      T=1.0-1.772454*D*EDSQ*(1.0-ERFD)
      BTHET=BTHET+(1.0-GUESP)*XKINV*XL*S
      BVAR=BVAR-(1.0-GUESP)*XKINV*XL*S**2*(T-GUESP*XL)
```

```
      RETURN
1     BTHET=BTHET-0.797885*(BVAR/SQRT(1.0/DIS**2+BVAR))*EDSQI*(1.0/(1.0+
     1ERFD))
      PART1=1.128379/(1.0+(1.0/DIS**2)*(1.0/BVAR))
      PART2=1.0/(EDSQ*(1.0+ERFD))**2
      PART3=0.564190+D*EDSQ*(1.0+ERFD)
      BVAR=BVAR*(1.0-PART1*PART2*PART3)
      RETURN
      END
      REAL FUNCTION ERFNP (X)
      DATA A1/0.254830/
      DATA A2/-0.284497/
      DATA A3/1.421414/
      DATA A4/-1.453152/
      DATA A5/1.061405/
      DATA P/0.327591/
      ERFNP=0.0
      IF (X.EQ.0.0) RETURN
      ES=SIGN(1.0,X)
      Y=ABS(X)
      IF (Y.LT.6.0) GO TO 1
      ERFNP=ES
      RETURN
1     Y2=Y*Y
      T=1.0/(1.0+P*Y)
      AT=((A1+(A2+(A3+(A4+A5*T)*T)*T)*T)*T)
      EAT=AT/EXP(Y2)
      ERFNP=(1.0-EAT)*ES
      RETURN
      END
      SUBROUTINE MAXLK (M,ITM,RESP,N,A,B,C,MAX,EPS,IFAIL,SDRV,THETA,TINF
     1O,EXPTOT,NUMITS,SEM)
      EXTERNAL FDDLOG,SDDLOG
      INTEGER RESP(M)
      DIMENSION A(N), B(N), C(N), ITM(M)
C***  USES MAXIMUM LIKELIHOOD LOGISTIC SCORING ALGORITHM AND RESPONSE
C***  MODEL
C***  BISECTION IS USED TO PROVIDE THE INITIAL GUESS FOR THE
C***  NEWTON-RAPHSON METHOD
      CALL BISECT (FDDLOG,RESP,A,B,C,M,ITM,5,GUESS)
C
      CALL NEWTRAP (FDDLOG,SDDLOG,RESP,A,B,C,M,ITM,MAX,EPS,NUMITS,GUESS,
     1THETA,SDRV,IFAIL)
C
      IF (IFAIL.EQ.1) 1,2
C***  NEWTON RAPHSON DID NOT CONVERGE
1     CALL NWTERR (THETA,SDRV,SEM,TINFO,EXPTOT)
      RETURN
C
2     CALL LGSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      SEM=1.0/SQRT(ABS(SDRV))
      RETURN
      END
      FUNCTION FDDLOG (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA XMAX,XMIN/200.0,-200.0/
      DATA D,RIGHT/1.7,1/
C***  CALCULATES FIRST DERIVATIVE OF LOG-LIKELIHOOD FUNCTION OF A
C***  RESPONSE VECTOR FOR THE LOGISTIC MODEL
      SUM=0.0
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      X=D*A(I)*(THETA-B(I))
      IF (X.LT.XMIN) X=XMIN
      IF (X.GT.XMAX) X=XMAX
```

```
      EXF=EXP(X)
      AE=A(I)*EXF
      SUM=SUM-AE/(EXF+1.0)
      IF (RESP(I).NE.RIGHT) GO TO 1
      CE=C(I)+EXF
      SUM=SUM+AE/CE
1     CONTINUE
      FDDLOG=-1.7*SUM
      RETURN
      END
      FUNCTION SDDLOG (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION ITM(M), A(M), B(M), C(M)
      DATA XMAX,XMIN/200.0,-200.0/
      DATA D,RIGHT/1.7,1/
C***  CALCULATES SECOND DERIVATIVE OF LOG-LIKELIHOOD FUNCTION
C***  OF A RESPONSE VECTOR FOR THE LOGISTIC MODEL
      SUM=0.0
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      X=D*A(I)*(THETA-B(I))
      IF (X.LT.XMIN) X=XMIN
      IF (X.GT.XMAX) X=XMAX
      EXF=EXP(X)
      AE=A(I)*EXF
      SUM=SUM-A(I)*AE/((1.0+EXF)*(1.0+EXF))
      IF (RESP(I).NE.RIGHT) GO TO 1
      CE=C(I)+EXF
      SUM=SUM+A(I)*C(I)*AE/(CE*CE)
1     CONTINUE
      SDDLOG=-2.89*SUM
      RETURN
      END
      SUBROUTINE BISECT (F1,RESP,A,B,C,M,ITM,NITER,BMID)
      INTEGER RESP(M)
      DIMENSION A(M), B(M), C(M), ITM(M)
C***  CALCULATES APPROXIMATE ROOT OF F1 BY BISECTION;
C***  BISECTING NITER (NUMBER OF ITERATIONS) TIMES.
C***  BMID IS BEST CURRENT GUESS AT ROOT THETA
C
C***  INITIALIZE LEFT BOUND AND F1(BOUND) AND RIGHT BOUND F1(BOUND)
      BL=-5.0
      BR=5.0
      BMID=0.0
      TL=F1(RESP,ITM,A,B,C,M,BL)
      TR=F1(RESP,ITM,A,B,C,M,BR)
C***  TEST FOR NO ROOT IN INTERVAL--RETURN IF NO  SOLUTION
      IF ((TL*TR).GT.0.0) RETURN
C
C***  NOW CALCULATE BISECTIONS NITER TIMES
      DO 3 I=1,NITER
      TMID=F1(RESP,ITM,A,B,C,M,BMID)
      IF ((TMID*TL).GT.0.0) GO TO 1
C***  REPLACE RIGHT BOUND WITH BMID
      BR=BMID
      GO TO 2
C***  REPLACE LEFT BOUND WITH BMID
1     TL=TMID
      BL=BMID
C***  FIND NEW MIDPOINT BMID
2     BMID=(BL+BR)/2.0
3     CONTINUE
      RETURN
      END
      SUBROUTINE NEWTRAP (F1,F2,RESP,A,B,C,M,ITM,NITER,EPS,NUMITS,GUESS,
     1THETA,SDRV,IFAIL)
```

```
      INTEGER RESP(M)
      DIMENSION A(M), B(M), C(M), ITM(M)
C***  CALCULATES THE ROOT OF F1 GIVEN ITS FIRST DERIVATIVE F2
C***  AND AN INITIAL GUESS USING NEWTON-RAPHSON METHOD
C***  THETA IS APPR. TO THE ROOT: SDRV IS F2(THETA)
      NUMITS=0
      THETA=GUESS
C***  LOOP UNTIL ERR<EPS OR NUMBER OF ITERATIONS BECOMES TOO LARGE
1     FDRV=F1(RESP,ITM,A,B,C,M,THETA)
      SDRV=F2(RESP,ITM,A,B,C,M,THETA)
      ERR=FDRV/SDRV
      THETA=THETA-ERR
      NUMITS=NUMITS+1
C***  EXIT LOOP CRITERION
      IF ((NUMITS.LT.NITER).AND.(ABS(ERR).GT.EPS)) GO TO 1
C***  END LOOP.  TEST FOR CONVERGENCE AND SET IFAIL
      IFAIL=0
      IF (ABS(ERR).LT.EPS) RETURN
C
C***  NEWTON RAPHSON METHOD DOES NOT CONVERGE
      IFAIL=1
      RETURN
      END
      SUBROUTINE NWTERR (THETA,SFORM,SEM,TINFO,EXPTOT)
C***  SETS ERROR VALUES FOR THE CASE IN WHICH NEWTON RAPHSON FAILS
C***  TO CONVERGE
      THETA=-99.99
      SFORM=-99.99
      SEM=-99.99
      TINFO=-99.99
      EXPTOT=-99.99
      RETURN
      END
      SUBROUTINE LGSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA XMAX,XMIN/12.0,-12.0/
      TINFO=0.0
      EXPTOT=0.0
      KOUNT=0
C
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      KOUNT=KOUNT+1
      ARGU=-1.7*A(I)*(THETA-B(I))
      IF (ARGU.GT.XMAX) ARGU=XMAX
      IF (ARGU.LT.XMIN) ARGU=XMIN
      P=C(I)+(1.0-C(I))*(1.0/(1.0+EXP(ARGU)))
      Q=1.0-P
      EARG=EXP(-ARGU)
      PPRIME=EARG/((1.0+EARG)*(1.0+EARG))
      PPRIME=PPRIME*(1.0-C(I))*A(I)*1.7
      TINFO=TINFO+(PPRIME*PPRIME)/(P*Q)
      EXPTOT=EXPTOT+P
1     CONTINUE
      EXPTOT=EXPTOT/FLOAT(KOUNT)
      RETURN
      END
      SUBROUTINE MAYLNO (RESP,ITM,M,N,A,B,C,MAX,EPS,THETA,SDRV,IFAIL,TIN
     1FO,EXPTOT,NUMITS,SEM)
      EXTERNAL FDNOGV,SDNOGV
      INTEGER RESP(M)
      DIMENSION ITM(N), A(N), B(N), C(N)
C***  USES MAXIMUM LIKELIHOOD NORMAL OGIVE SCORING ALGORITHM AND
C***  RESPONSE VECTOR
C***  BISECTION IS USED TO PROVIDE THE INITIAL GUESS FOR THE
C***  NEWTON RAPHSON METHOD
```

```
C
      CALL BISECT (FDNOGV,RESP,A,B,C,M,ITM,5,GUESS)
C
      CALL NEWTRAP (FDNOGV,SDNOGV,RESP,A,B,C,M,ITM,MAX,EPS,NUMITS,GUESS,
     1THETA,SDRV,IFAIL)
      IF (IFAIL.EQ.1) 1,2
C***  NEWTON RAPHSON DID NOT CONVERGE
1     CALL NWTERR (THETA,SDRV,SEM,TINFO,EXPTOT)
      RETURN
C
2     CALL NOSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      SDRV=ABS(SDRV)
      SEM=1.0/SQRT(SDRV)
      RETURN
      END
      FUNCTION FDNOGV (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA PI,RIGHT/3.141592,1/
      DATA XMAX,XMIN/7.0,-7.0/
C***  CALCULATES FIRST DERIVATIVE OF LOG-LIKELIHOOD FUNCTION OF
C***  A RESPONSE VECTOR FOR THE NORMAL OGIVE MODEL
C
      SUM=0.0
      ROOTPI=1.0/SQRT(2.0*PI)
      DO 2 I=1,M
      IF (ITM(I).EQ.0) GO TO 2
      TEMP=A(I)*(THETA-B(I))
      IF (TEMP.GT.XMAX) TEMP=XMAX
      IF (TEMP.LT.XMIN) TEMP=XMIN
      X=-(TEMP*TEMP)/2.0
      DNMRAT=ROOTPI*A(I)*(1.0-C(I))*EXP(X)
      DENOM=C(I)+(1.0-C(I))*CDFN(TEMP)
      IF (RESP(I).EQ.RIGHT) GO TO 1
      DENOM=-(1.0-DENOM)
1     SUM=SUM+(DNMRAT/DENOM)
2     CONTINUE
      FDNOGV=SUM
      RETURN
      END
      FUNCTION SDNOGV (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA PI,RIGHT/3.141592,1/
      DATA XMAX,XMIN/7.0,-7.0/
C***  CALCULATES SECOND DERIVATIVE OF LOG-LIKELIHOOD FUNCTION
C***  OF A RESPONSE VECTOR FOR THE NORMAL OGIVE MODEL
C
      SUM=0.0
      ROOTPI=1.0/SQRT(2.0*PI)
      DO 2 I=1,M
      IF (ITM(I).EQ.0) GO TO 2
      TEMP1=A(I)*(THETA-B(I))
      IF (TEMP1.GT.XMAX) TEMP1=XMAX
      IF (TEMP1.LT.XMIN) TEMP1=XMIN
      X=-TEMP1*TEMP1/2.0
      TEMP2=ROOTPI*(1.0-C(I))*A(I)*EXP(X)
      FIRNUM=TEMP2*TEMP2
      SECNUM=TEMP2*A(I)*TEMP1
      SDENOM=C(I)+(1.0-C(I))*CDFN(TEMP1)
      FDENOM=SDENOM*SDENOM
      IF (RESP(I).EQ.RIGHT) GO TO 1
      FDENOM=(1.0-SDENOM)*(1.0-SDENOM)
      SDENOM=-(1.0-SDENOM)
1     SUM=SUM-(FIRNUM/FDENOM)-(SECNUM/SDENOM)
2     CONTINUE
```

```
      SDNDGV=SUM
      RETURN
      END
      SUBROUTINE NOSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA PI/3.141592/
      DATA XMAX,XMIN/7.0,-7.0/
      TINFO=0.0
      EXPTOT=0.0
      KOUNT=0
C
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      KOUNT=KOUNT+1
      TEMP=A(I)*(THETA-B(I))
      IF (TEMP.GT.XMAX) TEMP=XMAX
      IF (TEMP.LT.XMIN) TEMP=XMIN
      P=C(I)+(1.0-C(I))*CDFN(TEMP)
      Q=1.0-P
      TEMP=-TEMP*TEMP/2.0
      PPRIME=(1.0/SQRT(2.0*PI))*(1.0-C(I))*A(I)*EXP(TEMP)
      TINFO=TINFO+(PPRIME*PPRIME)/(P*Q)
      EXPTOT=EXPTOT+P
    1 CONTINUE
      EXPTOT=EXPTOT/KOUNT
      RETURN
      END
```

APPENDIX D

ADADSCO FORTRAN PROGRAM LISTING

```
      PROGRAM ADADSCO (INPUT,OUTPUT,DATA,IPOOL,TAPE1=DATA,TAPE2=IPOOL,TA
     1PE3)
      DIMENSION ITEM(600), A(600), B(600), C(600), KEY(600), IREJ(80), I
     1FORM2(8), IRAW(80), INADS(80), IRESP(80), ADM(80), BDM(80), CDM(80
     2), DESC(24), NAME(2), IFORM1(8)
      INTEGER OPT1,OPT2,OPT3,OPT4
      REAL ITOT
      N=NC=0
C***********************************************************************
C                                                                      *
CREAD OPTIONS AND PROGRAM PARAMETER FROM INPUT FILE, DATA IS ON TAPE2  *
C                                                                      *
C***********************************************************************
      IPOOL=2
      READ 20, INUP,MMAX,OPT1,OPT2,OPT3,OPT4,TS,TSS,AMAX,BMIN,BMAX,CMAX,
     1IFLAG,IOMIT
      READ 22, (IFORM1(I),I=1,8)
C        IFORM1  IS THE VARIABLE FORMAT FOR THE ITEM POOL
      READ (IPOOL,IFORM1) (ITEM(I),A(I),B(I),C(I),KEY(I),I=1,INUP)
C***********************************************************************
C                                                                     *
C                                                                      *
CSTART READING THE SPECIFIC DATA (SPECIFIC FOR THE RUN) FROM THE INPUT *
CINAD IS THE ITEM ID#S ADMINISTERED                                    *
CIREJ IS THE REJECTED ITEM ID S                                        *
CIRESP IS THE RESPONSE VECTOR                                          *
C                                                                      *
C                                                                      *
C***********************************************************************
      READ 21, MNUM,(IREJ(I),I=1,MNUM)
      READ 22, (IFORM2(I),I=1,8)
C           IFORM2 IS THE VARIABLE FORMAT FOR THE SUBJECT DATA
C
      READ 24, DESC
      PRINT 23, INUP,MMAX,IOMIT,IFLAG,OPT1,OPT2,OPT3,OPT4,TS,TSS,AMAX,BM
     1AX,BMIN,CMAX,IFORM1,IFORM2,DESC
C***********************************************************************
C                                                                      *
C                                                                      *
CREAD A SUBJECT FROM TAPE1 CALCULATE THETA, LOOP BACK TO 5 ETC.        *
C                                                                      *
C                                                                      *
C***********************************************************************
1     READ (1,IFORM2) ID,NAME,M,(IRESP(I),I=1,MMAX),(INADS(I),I=1,MMAX)
      M=MINO(M,MMAX)
      IO=UNIT(1)
C     CHECK THE  END OF FILE ON DATA FILE
C
      IF (IO.LE.0) GO TO 2
      PRINT 25, IO
2     IF (IO.EQ.0) GO TO 19
      N=N+1
      ITOT=0.0
C        SET THE ITEM ID TO ZERO FOR THE OMMISSIONS (THAT IS READ IN FRO
C
C        AND SET THE RESPONSE VECTOR TO 1 IF THE ANSWER IS CORRECT
      DO 5 I=1,M
C        SET THE ITEM IDS IN IREEJ TO ZERO
      IF (MNUM.EQ.0) GO TO 4
      DO 3 IJ=1,MNUM
      IF (INADS(I).NE.IREJ(IJ)) GO TO 3
      INADS(I)=0
      GO TO 5
3     CONTINUE
4     CONTINUE
      IF (IRESP(I).EQ.IOMIT) INADS(I)=0
```

```
      IF (INADS(I).EQ.0) GO TO 5
      CALL SEARCH (INUP,INADS(I),ADM(I),BDM(I),CDM(I),KKE,ITEM,A,B,C,KEY
     1,ID)
C     IF THE FLAG IFLAG IS NOT ZERO IT IS TAKEN TO BE THE DUMMY KEY
C     IF IT IS ZERO THEN KEY IS READ FROM THE POOL AN LEFT IN KKE
      IF (IFLAG.NE.0) KKE=IFLAG
      IRES=0
      IF (IRESP(I).EQ.KKE) IRES=1
      IRESP(I)=IRES
5     CONTINUE
C*********************************************************************
C                                                                    *
C                                                                    *
CIN THE NEXT DO LOOP THE ITEM PARAMETERS CORRESPONDING TO THE ITEMS  *
CIN INAD ARE RETRIVED FROM A,B,C, AND LOADED INTO ADM,BDM,CDM RESP.  *
CTHE ENTRIES IN THE ADM,BDM,CDM ARE ZEROED FOR THE CASE OF ZERO ITEM *
CID IN THE INAD                                                      *
C                                                                    *
C                                                                    *
C*********************************************************************
C         IF OPTION 3 IS ON THE PARAMETERS A,B,C ARE CONSTRAINED WITHIN B
C         OF AMAX,AMIN,BMAX,BMIN,CMAX
      IF (OPT3.EQ.0) GO TO 7
      DO 6 I=1,M
      IF (INADS(I).EQ.0) GO TO 6
      IF ((ADM(I).GT.AMAX).OR.(OPT3.EQ.3)) ADM(I)=AMAX
      IF (BDM(I).LT.BMIN) BDM(I)=BMIN
      IF (BDM(I).GT.BMAX) BDM(I)=BMAX
      IF ((CDM(I).GT.CMAX).OR.(OPT3.EQ.2)) CDM(I)=CMAX
6     CONTINUE
C        OPTION 1 WILL PRINT THE SPECIFIC DATA IF ITS ON
C
7     CONTINUE
      IF ((OPT1.EQ.0).OR.(OPT1.GT.10)) GO TO 8
      OPT1=OPT1+1
      PRINT 26, ID,NAME,(INADS(II),IRESP(II),ADM(II),BDM(II),CDM(II),II=
     11,M)
8     CONTINUE
      ITINADS=0
      DO 9 KK=1,M
      ITOT=ITOT+IRESP(KK)
9     IF (INADS(KK).EQ.0) ITINADS=ITINADS+1
      KL=M-ITINADS
      ITOT=ITOT/FLOAT((KL))
      IF (ITOT.EQ.0) 10,11
10    PRINT 27, NAME,ID
      IF (OPT4.EQ.3) GO TO 13
      T=-10.0
      SFORM=0.0
      TINFO=0.0
      EXPTOT=0.0
      SEM=0.0
      ITER=0
      IKL=KL
      GO TO 18
11    IF (ITOT.EQ.1.0) 12,13
12    PRINT 31, NAME,ID
      IF (OPT4.EQ.3) GO TO 13
      T=10.0
      SFORM=0.0
      TINFO=0.0
      EXPTOT=0.0
      SEM=0.0
      ITER=0
      IKL=KL
      GO TO 18
```

```
C*********************************************************************
C                                                                    *
C                                                                    *
C     NOW THE DATA IS READY TO MAKE THE CALLS TO THE APPROPRIATE ROUTINE
CTO ESTIMATE THE THETA. OPTIN 4 WILL DETERMINE THE METHOD BY WHICH   *
CTHE THETA ESTIMATE WILL BE FOUND                                    *
C                                                                    *
C                                                                    *
C*********************************************************************
13    IKL=KL
      IF (OPT4-2) 14,15,16
14    CALL MAXLNO (IRESP,INADS,M,M,ADM,BDM,COM,50,.005,T,SFORM,IFAIL,TIN
     1FO,EXPTOT,ITER,SEM)
      GO TO 17
15    CALL MAXLK (M,INADS,IRESP,M,ADM,BDM,COM,50,.005,IFAIL,SFORM,T,TINF
     1O,EXPTOT,ITER,SEM)
C
      GO TO 17
16    T=TS
      SFORM=TSS
      CALL BAYES (M,INADS,IRESP,M,ADM,BDM,COM,T,SFORM,TINFO,EXPTOT)
      ITER=0
      SEM=0.0
      GO TO 18
17    IF (IFAIL.EQ.0) GO TO 18
      PRINT 28, NAME,ID
C      SFORM AND T ARE SET TO -99.99 IN MAXLK IF NOT CONV
      NC=NC+1
C*********************************************************************
C                                                                    *
CWRITE THE SUCCESFUL RESULTS TOTHE FILE TAPE3                        *
C                                                                    *
C*********************************************************************
18    WRITE (3,29) NAME,ID,ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER,SEM
      GO TO 1
19    PRINT 30, N,NC
C
      STOP
C
C
20    FORMAT (2I4,X,4I1,6F5.2,I2,I2)
21    FORMAT (16I5)
22    FORMAT (8A10)
23    FORMAT (T50,*ADADSCO*,/,T50*========*,//////,T20,*ADAPTIVE DICHOTOM
     1US SCORING WITH THREE PARAMETER MODELS*,////,T40*PSYCHOMETRIC METH
     2ODS PROGRAM*,/,T40*DEPARTMENT OF PSYCHOLOGY*,/,T40*UNIVERSITY OF M
     3INNESOTA*,/,T40*MPLS. MINN. 55455*,/,///,T20*INUP*,T27*=*I5,/,T20,
     4*MMAX*,T27*=*I5,/,T20,*IOMIT*,T27*=*,I5,/,T20*IFLAG*,T27*=*,I5,/,T
     520*OPT1*,T27*=*I5,/,T20*OPT2*,T27*=*I5,/,T20*OPT3*,T27*=*I5,/,T20*
     6OPT4*,T27*=*,I5,/,T20*TS*,T27*=*F5.2,/,T20*TSS*,T27*=*F5.2,/,T20*A
     7MAX*,T27*=*F5.2,/,T20,*BMAX*,T27,*=*F5.2,/,T20*BMIN*,T27,*=*F5.2,/
     8,T20*CMAX*,T27,*=*F5.2,/,T20,*VARIABLE FORMAT FOR POOL=*8A10,/,T20
     9,*VARIABLE FORMAT FOR DATA=*8A10,/,T20,8A10,/,T20,8A10,/,T20,8A10,
     */)
24    FORMAT (8A10)
25    FORMAT (10X,*PARITY ERROR ON TAPE*,90X,I2)
26    FORMAT (10X,A9,2A10,/,(1X,I4,2X,I2,2X,3F10.2))
27    FORMAT (10X,* SUBJECT *,2A10,*ID= *,A9,*HAS NO RIGHT ANSWERS*)
28    FORMAT (10X,* MAXIMUM LIKELIHOOD ESTIMATION DOES NOT CONVERGE*,* F
     1OR THE SUBJECT = *,2A10,*  ID= *,A9)
29    FORMAT (X,2A10,A9,F5.2,2F7.2,I4,2F7.2,I4,F7.2)
30    FORMAT (10X,* CASES  READ=*,I5,* CASES NOT  CONVERGED=*,I5)
31    FORMAT (10X,* SUBJECT *,2A10,*ID= *,A9,*HAS ALL ANSWERS RIGHT*)
      END
      SUBROUTINE SEARCH (INUP,ID,A,B,C,KEY,ITM,AP,BP,CP,KEYP,IDNUM)
      DIMENSION AP(INUP), BP(INUP), CP(INUP), KEYP(INUP), ITM(INUP)
```

```
      INTEGER FLAG
      DO 1 I=1,INUP
      IF (ID.NE.ITM(I)) GO TO 1
      A=AP(I)
      B=BP(I)
      C=CP(I)
      KEY=KEYP(I)
      CALL PCHECK (A,B,C,ID,IDNUM)
      RETURN
 1    CONTINUE
      PRINT 2, ID,IDNUM
C
      ID=0
      RETURN
C
C
C
 2    FORMAT (10X,* ITEM =*,I4,* IS NOT IN THE POOL FOR SUBJECT ID =*,A9
     1)
      END
      SUBROUTINE PCHECK (A,B,C,ID,IDNUM)
C***  CHECK WHETHER OR NOT ITEM PARAMETERS ARE VALID
C***  IF NOT, ERROR MESSAGE IS PRINTED
C
      IF (A.LE.0.0) PRINT 1, ID,A,IDNUM
      IF ((-5.0.GT.B).OR.(B.GT.5.0)) PRINT 2, ID,B,IDNUM
      IF ((0.0.GT.C).OR.(C.GT.1.0)) PRINT 3, ID,C,IDNUM
      RETURN
C
C
C
 1    FORMAT (10X,*ITEM =*,I4,* HAS THE INVALID A PARAMETER OF *,F5.2,*
     1  A MUST BE GREATER THAN 0.0*,/10X,*ERROR FOUND *,*FOR THE SUBJECT
     2 WITH ID =*,A9)
 2    FORMAT (10X,*ITEM =*,I4,* HAS THE EXTREME B PARAMETER OF *,F5.2,5X
     1,*ERROR FOUND FOR THE SUBJECT WITH ID =*,A9)
 3    FORMAT (10X,*ITEM =*,I4,* HAS THE INVALID C PARAMETER OF *,F5.2,*
     1  C MUST BE BETWEEN 0.0 AND 1.0*,/10X,*ERROR FOUND *,*FOR THE SUBJ
     2ECT WITH ID =*,A9)
      END
      SUBROUTINE BAYES (M,ITM,RESP,N,A,B,C,BTHET,BVAR,TINFO,EXPTOT)
      INTEGER RESP(M),ITM(M)
      REAL A(N),B(N),C(N)
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      CALL BSCOR (BTHET,BVAR,B(I),A(I),C(I),RESP(I))
 1    CONTINUE
      CALL NOSTAT (M,ITM,A,B,C,BTHET,TINFO,EXPTOT)
      RETURN
      END
      SUBROUTINE BSCOR (BTHET,BVAR,DIF,DIS,GUESP,IRESP)
      D=(DIF-BTHET)/SQRT(2.0*(1.0/DIS**2+BVAR))
      ERFD=ERFNP(D)
      EDSQ=EXP(D**2)
      IF (EDSQ.EQ.0.0) RETURN
      EDSQI=1.0/EDSQ
      XKINV=0.5*(1.0-ERFD)
      XLINV=GUESP+(1.0-GUESP)*XKINV
      IF ((XLINV.EQ.0.0).OR.(XKINV.EQ.0.0)) RETURN
      XL=1.0/XLINV
      IF (IRESP.NE.1) GO TO 1
      S=0.398942*(SQRT(BVAR)/SQRT(1.0+(1.0/DIS**2)/BVAR))*(1.0/XKINV)*ED
     1SQI
      T=1.0-1.772454*D*EDSQ*(1.0-ERFD)
      BTHET=BTHET+(1.0-GUESP)*XKINV*XL*S
      BVAR=BVAR-(1.0-GUESP)*XKINV*XL*S**2*(T-GUESP*XL)
```

```
      RETURN
1     BTHET=BTHET-0.797885*(BVAR/SQRT(1.0/DIS**2+BVAR))*EDSQI*(1.0/(1.0+
     1ERFD))
      PART1=1.128379/(1.0+(1.0/DIS**2)*(1.0/BVAR))
      PART2=1.0/(EDSQ*(1.0+ERFD))**2
      PART3=0.564190+D*EDSQ*(1.0+ERFD)
      BVAR=BVAR*(1.0-PART1*PART2*PART3)
      RETURN
      END
      REAL FUNCTION ERFNP (X)
      DATA A1/0.254830/
      DATA A2/-0.284497/
      DATA A3/1.421414/
      DATA A4/-1.453152/
      DATA A5/1.061405/
      DATA P/0.327591/
      ERFNP=0.0
      IF (X.EQ.0.0) RETURN
      ES=SIGN(1.0,X)
      Y=ABS(X)
      IF (Y.LT.6.0) GO TO 1
      ERFNP=ES
      RETURN
1     Y2=Y*Y
      T=1.0/(1.0+P*Y)
      AT=((A1+(A2+(A3+(A4+A5*T)*T)*T)*T)*T)
      EAT=AT/EXP(Y2)
      ERFNP=(1.0-EAT)*ES
      RETURN
      END
      SUBROUTINE MAXLK (M,ITM,RESP,N,A,B,C,MAX,EPS,IFAIL,SDRV,THETA,TINF
     1O,EXPTOT,NUMITS,SEM)
      EXTERNAL FDDLOG,SDDLOG
      INTEGER RESP(M)
      DIMENSION A(N), B(N), C(N), ITM(M)
C***  USES MAXIMUM LIKELIHOOD LOGISTIC SCORING ALGORITHM AND RESPONSE
C***  MODEL
C***  BISECTION IS USED TO PROVIDE THE INITIAL GUESS FOR THE
C***  NEWTON-RAPHSON METHOD
      CALL BISECT (FDDLOG,RESP,A,B,C,M,ITM,5,GUESS)
C
      CALL NEWTRAP (FDDLOG,SDDLOG,RESP,A,B,C,M,ITM,MAX,EPS,NUMITS,GUESS,
     1THETA,SDRV,IFAIL)
C
      IF (IFAIL.EQ.1) 1,2
C***  NEWTON RAPHSON DID NOT CONVERGE
1     CALL NWTERR (THETA,SDRV,SEM,TINFO,EXPTOT)
      RETURN
C
2     CALL LGSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      SEM=1.0/SQRT(ABS(SDRV))
      RETURN
      END
      FUNCTION FDDLOG (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA XMAX,XMIN/200.0,-200.0/
      DATA D,RIGHT/1.7,1/
C***  CALCULATES FIRST DERIVATIVE OF LOG-LIKELIHOOD FUNCTION OF A
C***  RESPONSE VECTOR FOR THE LOGISTIC MODEL
      SUM=0.0
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      X=D*A(I)*(THETA-B(I))
      IF (X.LT.XMIN) X=XMIN
      IF (X.GT.XMAX) X=XMAX
```

```
      EXF=EXP(X)
      AE=A(I)*EXF
      SUM=SUM-AE/(EXF+1.0)
      IF (RESP(I).NE.RIGHT) GO TO 1
      CE=C(I)+EXF
      SUM=SUM+AE/CE
1     CONTINUE
      FDDLOG=-1.7*SUM
      RETURN
      END
      FUNCTION SDDLOG (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION ITM(M), A(M), B(M), C(M)
      DATA XMAX,XMIN/200.0,-200.0/
      DATA D,RIGHT/1.7,1/
C***  CALCULATES SECOND DERIVATIVE OF LOG-LIKELIHOOD FUNCTION
C***  OF A RESPONSE VECTOR FOR THE LOGISTIC MODEL
      SUM=0.0
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      X=D*A(I)*(THETA-B(I))
      IF (X.LT.XMIN) X=XMIN
      IF (X.GT.XMAX) X=XMAX
      EXF=EXP(X)
      AE=A(I)*EXF
      SUM=SUM-A(I)*AE/((1.0+EXF)*(1.0+EXF))
      IF (RESP(I).NE.RIGHT) GO TO 1
      CE=C(I)+EXF
      SUM=SUM+A(I)*C(I)*AE/(CE*CE)
1     CONTINUE
      SDDLOG=-2.89*SUM
      RETURN
      END
      SUBROUTINE BISECT (F1,RESP,A,B,C,M,ITM,NITER,BMID)
      INTEGER RESP(M)
      DIMENSION A(M), B(M), C(M), ITM(M)
C***  CALCULATES APPROXIMATE ROOT OF F1 BY BISECTION:
C***  BISECTING NITER (NUMBER OF ITERATIONS) TIMES.
C***  BMID IS BEST CURRENT GUESS AT ROOT THETA
C
C***  INITIALIZE LEFT BOUND AND F1(BOUND) AND RIGHT BOUND F1(BOUND)
      BL=-5.0
      BR=5.0
      BMID=0.0
      TL=F1(RESP,ITM,A,B,C,M,BL)
      TR=F1(RESP,ITM,A,B,C,M,BR)
C***  TEST FOR NO ROOT IN INTERVAL--RETURN IF NO  SOLUTION
      IF ((TL*TR).GT.0.0) RETURN
C
C***  NOW CALCULATE BISECTIONS NITER TIMES
      DO 3 I=1,NITER
      TMID=F1(RESP,ITM,A,B,C,M,BMID)
      IF ((TMID*TL).GT.0.0) GO TO 1
C***  REPLACE RIGHT BOUND WITH BMID
      BR=BMID
      GO TO 2
C***  REPLACE LEFT BOUND WITH BMID
1     TL=TMID
      BL=BMID
C***  FIND NEW MIDPOINT BMID
2     BMID=(BL+BR)/2.0
3     CONTINUE
      RETURN
      END
      SUBROUTINE NEWTRAP (F1,F2,RESP,A,B,C,M,ITM,NITER,EPS,NUMITS,GUESS,
     1THETA,SDRV,IFAIL)
```

```
      INTEGER RESP(M)
      DIMENSION A(M), B(M), C(M), ITM(M)
C***  CALCULATES THE ROOT OF F1 GIVEN ITS FIRST DERIVATIVE F2
C***  AND AN INITIAL GUESS USING NEWTON-RAPHSON METHOD
C***  THETA IS APPR. TO THE ROOT; SDRV IS F2(THETA)
      NUMITS=0
      THETA=GUESS
C***  LOOP UNTIL ERR<EPS OR NUMBER OF ITERATIONS BECOMES TOO LARGE
1     FDRV=F1(RESP,ITM,A,B,C,M,THETA)
      SDRV=F2(RESP,ITM,A,B,C,M,THETA)
      ERR=FDRV/SDRV
      THETA=THETA-ERR
      NUMITS=NUMITS+1
C***  EXIT LOOP CRITERION
      IF ((NUMITS.LT.NITER).AND.(ABS(ERR).GT.EPS)) GO TO 1
C***  END LOOP.  TEST FOR CONVERGENCE AND SET IFAIL
      IFAIL=0
      IF (ABS(ERR).LT.EPS) RETURN
C
C***  NEWTON RAPHSON METHOD DOES NOT CONVERGE
      IFAIL=1
      RETURN
      END
      SUBROUTINE SWIERR (THETA,SFORM,SEM,TINFO,EXPTOT)
C***  SETS ERROR VALUES FOR THE CASE IN WHICH NEWTON RAPHSON FAILS
C***  TO CONVERGE
      THETA=-99.99
      SFORM=-99.99
      SEM=-99.99
      TINFO=-99.99
      EXPTOT=-99.99
      RETURN
      END
      SUBROUTINE LGSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA XMAX,XMIN/12.0,-12.0/
      TINFO=0.0
      EXPTOT=0.0
      KOUNT=0
C
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      KOUNT=KOUNT+1
      ARGU=-1.7*A(I)*(THETA-B(I))
      IF (ARGU.GT.XMAX) ARGU=XMAX
      IF (ARGU.LT.XMIN) ARGU=XMIN
      P=C(I)+(1.0-C(I))*(1.0/(1.0+EXP(ARGU)))
      Q=1.0-P
      EARG=EXP(-ARGU)
      PPRIME=EARG/((1.0+EARG)*(1.0+EARG))
      PPRIME=PPRIME*(1.0-C(I))*A(I)*1.7
      TINFO=TINFO+(PPRIME*PPRIME)/(P*Q)
      EXPTOT=EXPTOT+P
1     CONTINUE
      EXPTOT=EXPTOT/KOUNT
      RETURN
      END
      SUBROUTINE MAXLNO (RESP,ITM,M,N,A,B,C,MAX,EPS,THETA,SDRV,IFAIL,TIN
     1FO,EXPTOT,NUMITS,SEM)
      EXTERNAL FDNOGV,SDNOGV
      INTEGER RESP(M)
      DIMENSION ITM(N), A(N), B(N), C(N)
C***  USES MAXIMUM LIKELIHOOD NORMAL OGIVE SCORING ALGORITHM AND
C***  RESPONSE VECTOR
C***  BISECTION IS USED TO PROVIDE THE INITIAL GUESS FOR THE
C***  NEWTON RAPHSON METHOD
```

```
C
      CALL BISECT (FDNOGV,RESP,A,B,C,M,ITM,5,GUESS)
C
      CALL NEWTRAP (FDNOGV,SDNOGV,RESP,A,B,C,M,ITM,MAX,EPS,NUMITS,GUESS,
     1THETA,SDRV,IFAIL)
      IF (IFAIL.EQ.1) 1,2
C***  NEWTON RAPHSON DID NOT CONVERGE
1     CALL NWTERR (THETA,SDRV,SEM,TINFO,EXPTOT)
      RETURN
C
2     CALL NOSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      SDRV=ABS(SDRV)
      SEM=1.0/SQRT(SDRV)
      RETURN
      END
      FUNCTION FDNOGV (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA PI,RIGHT/3.141592,1/
      DATA XMAX,XMIN/7.0,-7.0/
C***  CALCULATES FIRST DERIVATIVE OF LOG-LIKELIHOOD FUNCTION OF
C***  A RESPONSE VECTOR FOR THE NORMAL OGIVE MODEL
C
      SUM=0.0
      ROOTPI=1.0/SQRT(2.0*PI)
      DO 2 I=1,M
      IF (ITM(I).EQ.0) GO TO 2
      TEMP=A(I)*(THETA-B(I))
      IF (TEMP.GT.XMAX) TEMP=XMAX
      IF (TEMP.LT.XMIN) TEMP=XMIN
      X=-(TEMP*TEMP)/2.0
      DNMRAT=ROOTPI*A(I)*(1.0-C(I))*EXP(X)
      DENOM=C(I)+(1.0-C(I))*CDFN(TEMP)
      IF (RESP(I).EQ.RIGHT) GO TO 1
      DENOM=-(1.0-DENOM)
1     SUM=SUM+(DNMRAT/DENOM)
2     CONTINUE
      FDNOGV=SUM
      RETURN
      END
      FUNCTION SDNOGV (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA PI,RIGHT/3.141592,1/
      DATA XMAX,XMIN/7.0,-7.0/
C***  CALCULATES SECOND DERIVATIVE OF LOG-LIKELIHOOD FUNCTION
C***  OF A RESPONSE VECTOR FOR THE NORMAL OGIVE MODEL
C
      SUM=0.0
      ROOTPI=1.0/SQRT(2.0*PI)
      DO 2 I=1,M
      IF (ITM(I).EQ.0) GO TO 2
      TEMP1=A(I)*(THETA-B(I))
      IF (TEMP1.GT.XMAX) TEMP1=XMAX
      IF (TEMP1.LT.XMIN) TEMP1=XMIN
      X=-TEMP1*TEMP1/2.0
      TEMP2=ROOTPI*(1.0-C(I))*A(I)*EXP(X)
      FIRNUM=TEMP2*TEMP2
      SECNUM=TEMP2*A(I)*TEMP1
      SDENOM=C(I)+(1.0-C(I))*CDFN(TEMP1)
      FDENOM=SDENOM*SDENOM
      IF (RESP(I).EQ.RIGHT) GO TO 1
      FDENOM=(1.0-SDENOM)*(1.0-SDENOM)
      SDENOM=-(1.0-SDENOM)
1     SUM=SUM-(FIRNUM/FDENOM)-(SECNUM/SDENOM)
2     CONTINUE
```

```
      SDNOGV=SUM
      RETURN
      END
      SUBROUTINE NOSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA XMAX,XMIN/7.0,-7.0/
      DATA PI/3.141592/
      TINFO=0.0
      EXPTOT=0.0
      KOUNT=0
C
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      KOUNT=KOUNT+1
      TEMP=A(I)*(THETA-B(I))
      IF (TEMP.GT.XMAX) TEMP=XMAX
      IF (TEMP.LT.XMIN) TEMP=XMIN
      P=C(I)+(1.0-C(I))*CDFN(TEMP)
      Q=1.0-P
      TEMP=-TEMP*TEMP/2.0
      PPRIME=(1.0/SQRT(2.0*PI))*(1.0-C(I))*A(I)*EXP(TEMP)
      TINFO=TINFO+(PPRIME*PPRIME)/(P*Q)
      EXPTOT=EXPTOT+P
1     CONTINUE
      EXPTOT=EXPTOT/KOUNT
      RETURN
      END
```

APPENDIX E
LINPSCO FORTRAN PROGRAM LISTING

```
      PROGRAM LINPSCO (INPUT,OUTPUT,DATA,IPOOL,TAPE1=DATA,TAPE2=IPOOL,TA
     1PE3,PUNCH)
C*********************************************************************
C               DEFINITION OF VARIABLES USED IN LINPSCO
C
C     T=THETA:  THE ABILITY ESTIMATE
C     ITEM:  AN ARRAY OF THE ITEMS IN THE ITEM POOL
C     INUP:  THE NUMBER OF ITEMS IN THE ITEM POOL
C     A:  AN ARRAY OF THE DISCRIMINATION PARAMETER(S) ASSOCIATED WITH
C        EACH ITEM
C   B:  AN ARRAY OF THE DIFFICULTY PARAMETERS ASSOCIATED WITH EACH ITEM
C     MAXCAT:  NO. OF RESPONSE CATEGORIES MINUS 1 FOR THE ITEM IN THE
C            ITEM POOL WHICH HAS THE MAXIMUM NO. OF RESPONSE
C            CATEGORIES
C     INAD:  AN ARRAY OF THE ITEMS WHICH HAVE BEEN ADMINISTERED TO ALL
C          SUBJECTS
C     M:  THE NUMBER OF ITEMS IN THE TEST
C     ADM AND BDM:  THE ARRAYS OF PARAMETERS ASSOCIATED WITH THE ITEMS
C                 IN INAD
C     INADS:  AN ARRAY OF THE ITEMS USED TO CALCULATE THETA FOR A GIVEN
C           SUBJECT (INADS=INAD-(REJECTION AND OMISSIONS) WHERE ID S
C           OF REJECTED OR OMITTED ITEMS ARE SET TO ZERO)
C     IRESP:  THE RESPONSE VECTOR OF THE CURRENT SUBJECT
C     NCAT:  AN ARRAY OF THE NUMBER OF RESPONSE CATEGORIES MINUS 1 FOR
C         EACH ITEM ADMINISTERED
C     PERCNT:  PERCENTAGE OF ITEMS ANSWERED BY A SUBJECT FOR WHICH THE
C            BEST RESPONSE HAS BEEN CHOSEN
C     D:  A CONSTANT USED TO CHANGE THE METRIC OF THE LOGISTIC GRADED
C       MODEL.  D=1.7 OR 1.0: THE DEFAULT VALUE IS 1.0
C
C*********************************************************************
      COMMON D
      DIMENSION ITEM(100), A(100,10), B(100,10), INAD(100), IREJ(100), I
     1RESP(100), ADM(100,10), BDM(100,10), NAME(2), IFORM(8), NCAT(100),
     2 IFORM1(8), INADS(100), DESC(24)
      INTEGER OPT1,OPT2,OPT4,ADIM,BDIM
      N=NC=0
C*********************************************************************
C                                                                    *
CREAD OPTIONS AND PROGRAM PARAMETER FROM INPUT FILE DATA IS ON TAPE2 *
C                                                                    *
C*********************************************************************
      IPOOL=2
      READ 30, INUP,M,MAXCAT,OPT1,OPT2,OPT4,D,IOMIT
      CALL CHKINP (INUP,M,OPT4)
      IF (D.NE.1.7) D=1.0
      READ 33, (IFORM1(I),I=1,8)
      READ 32, (NCAT(I),I=1,M)
C***  INPUT ITEMS AND THEIR PARAMETERS
      IKI=ADIM(MAXCAT,OPT4)
      K=BDIM(MAXCAT,OPT4)
      DO 1 I=1,INUP
1     READ (IPOOL,IFORM1) ITEM(I),(A(I,JJ),JJ=1,IKI),(B(I,J),J=1,K)
C
      READ 31, (INAD(I),I=1,M)
      READ 32, (IREJ(I),I=1,M)
      READ 33, (IFORM(I),I=1,8)
      READ 34, DESC
      PRINT 35, INUP,M,IOMIT,OPT1,OPT2,OPT4,MAXCAT,D,IFORM1,IFORM,DESC
C
C***  THOSE ITEM ID S WHICH ARE IN THE REJECTION VECTOR WILL BE SET
C***  TO ZERO.  ZERO ITEM ID S WILL BE SKIPPED DURING COMPUTATIONS
      DO 2 I=1,M
2     IF (IREJ(I).EQ.1) INAD(I)=0
      IF (OPT2.EQ.1) GO TO 10
C
```

```
C
C***   SEARCH FOR ITEMS ADMINISTERED IN POOL
       DO 9 J=1,M
       IKI=ADIM(NCAT(J),OPT4)
       K=BDIM(NCAT(J),OPT4)
       IF (INAD(J).NE.0) GO TO 5
C***   BLANK OR REJECTED ITEM ENCOUNTERED
       DO 3 L=1,IKI
3      ADM(J,L)=0.0
       DO 4 L=1,K
4      BDM(J,L)=0.0
       GO TO 9
5      CONTINUE
C
       DO 8 I=1,INUP
       IF (INAD(J).NE.ITEM(I)) GO TO 8
       DO 6 L=1,IKI
6      ADM(J,L)=A(I,L)
       DO 7 L=1,K
7      BDM(J,L)=B(I,L)
       GO TO 9
8      CONTINUE
       INAD(J)=0
9      CONTINUE
       GO TO 13
C
C***   ALL ITEMS IN POOL HAVE BEEN ADMINISTERED SO POOL DOES NOT
C***   NEED TO BE SEARCHED
10     DO 12 I=1,M
       IKI=ADIM(NCAT(I),OPT4)
       K=BDIM(NCAT(I),OPT4)
       DO 11 JJ=1,IKI
11     ADM(I,JJ)=A(I,JJ)
       DO 12 J=1,K
       BDM(I,J)=B(I,J)
12     CONTINUE
C
C
C***   PUNCH THE ITEM PARAMETERS EXTIMATES CORRESPONDING TO THE ITEMS
C***   IN THE TEST
13     IF (OPT1.NE.1) GO TO 15
       DO 14 I=1,M
       IF (INAD(I).EQ.0) GO TO 14
       IKI=ADIM(NCAT(I),OPT4)
       K=BDIM(NCAT(I),OPT4)
       PUNCH 36, INAD(I),IREJ(I),(ADM(I,JJ),JJ=1,IKI)
       PUNCH 37, (BDM(I,J),J=1,K)
14     CONTINUE
C
C      PRINT OUT THE ITEMS AND THEIR PARAMETERS
15     DO 16 III=1,M
       IKI=ADIM(NCAT(III),OPT4)
       K=BDIM(NCAT(III),OPT4)
       PRINT 39, INAD(III),IREJ(III),(ADM(III,JJ),JJ=1,IKI)
16     PRINT 40, (BDM(III,J),J=1,K)
       PRINT 43
C*********************************************************************
C***                                                                 *
C***   READ SUBJECT FROM TAPE1, CALCULATE THETA, LOOP BACK TO 300 UNTIL*
C***   THERE ARE NO MORE SUBJECTS TO SCORE                           *
C***                                                                 *
C*********************************************************************
       N=0
17     READ (1,IFORM) NAME,ID,(IRESP(I),I=1,M)
       IO=UNIT(1)
       IF (IO.LE.0) GO TO 18
```

```
      PRINT 38, IO
18    IF (IO.EQ.0) GO TO 29
C
C***  CHECK FOR VALID RESPONSES AND FOR SPECIAL RESPONSE VECTORS
      CALL CHKRSP (IRESP,IOMIT,INAD,NCAT,M,NAME,ID,INADS)
C
      CALL CHKVEC (IRESP,INADS,NCAT,M,ICHK,NBEST,NANS)
      GO TO (19,20,21,23), ICHK
C***  ALL ITEMS OMITTED
19    PRINT 45, NAME,ID
      T=-50.00
      PERCNT=-50.00
      GO TO 22
C***  ALL RESPONSES INCORRECT
20    PRINT 46, NAME,ID
      T=-10.0
      PERCNT=0.0
      GO TO 22
C***  ALL RESPONSES CORRECT
21    PRINT 47, NAME,ID
      T=10.0
      PERCNT=1.0
C
22    SFORM=0.0
      NUMITS=0
      TINFO=0.0
      GO TO 28
23    CONTINUE
C
      PERCNT=FLOAT(NBEST)/FLOAT(NANS)
C
C
C***  DETERMINE WHICH MODEL TO USE
      IF (OPT4-2) 24,25,26
24    CALL LOGRAD (IRESP,ADM,BDM,M,NCAT,INADS,.001,50,SFORM,IFAIL,T,NUMI
     1TS,TINFO,SE)
      GO TO 27
25    CALL NOGRAD (IRESP,ADM,BDM,M,NCAT,INADS,.001,50,SFORM,IFAIL,T,NUMI
     1TS,TINFO,SE)
      GO TO 27
26    CALL NOMLOG (IRESP,ADM,BDM,M,NCAT,INADS,.001,50,SFORM,IFAIL,T,NUMI
     1TS,TINFO,SE)
C
C***  OUTPUT RESULTS TO TAPE3
27    IF (IFAIL.EQ.0) GO TO 28
C***  CONVERGENCE NOT OBTAINED
      PRINT 41, NAME,ID
      NC=NC+1
C
28    WRITE (3,42) NAME,ID,PERCNT,T,SFORM,NANS,NUMITS,TINFO,SE
      N=N+1
      GO TO 17
C
29    PRINT 44, N,NC
      STOP
C
30    FORMAT (2I4,I1,2I1,1X,I1,F5.2,27X,I2)
31    FORMAT (16I5)
32    FORMAT (80I1)
33    FORMAT (8A10)
34    FORMAT (8A10)
35    FORMAT (T50,*LINPSCO*,/,T50*=======*,//////,T20,*LINEAR POLYCHOTOMU
     1S SCORING WITH TWO PARAMETER MODELS*,////,T40*PSYCHOMETRICS METHOD
     2S PROGRAM*,/,T40*DEPARTMENT OF PSYCHOLOGY*,/,T40*UNIVERSITY OF MIN
     3NESOTA*,/,T40*MPLS.  MINN. 55455*,////,T20,*INUP*,T27,*=*,I4,/,T20
     4,*MMAX*,T27,*=*I4,/,T20,*IOMIT*,T27,*=*,I4,/,T20*OPT1*,T27*=*I4,/,
```

```
     5T20*OPT2*,T27*=*,I4,/,T20*OPT4*,T27*=*,I4,/,T20,*MAXCAT*,T27,*=*,I
     64,/T20,*D*,T27,*=*,F4.1,/T20,*VARIABLE FORMAT*,* FOR POOL =*,8A10,
     7/T20,*VARIABLE FORMAT FOR DATA =*,8A10,/T20,8A10,/T20,8A10,/,T20,8
     8A10)
36    FORMAT (I5,1X,I2,2X,10F6.2)
37    FORMAT (10F6.2)
38    FORMAT (*PARITY ERROR ON TAPE*,100X,I2)
39    FORMAT (/10X,*ITEM ID = *,I5,5X,*REJECTION =*,I3,/10X,*A:  *,10F6.
     12)
40    FORMAT (12X,*B:  *,10F6.2)
41    FORMAT (10X,*CONVERGENCE NOT OBTAINED FOR SUBJECT =*,2A10,* ID =*,
     1A9)
42    FORMAT (1X,2A10,A9,F5.2,2F7.2,I4,I4,2F7.2)
43    FORMAT (////)
44    FORMAT (10X,*CASES READ =*,I5,*  CASES NOT CONVERGED =*,I5)
45    FORMAT (10X,*ALL ITEMS OMITTED FOR SUBJECT =*,2A10,* ID =*,A9)
46    FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS ALL ANSWERS IN*,*COR
     1RECT*)
47    FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS ALL ANSWERS COR*,*RE
     1CT*)
      END
      INTEGER FUNCTION ADIM (NUMCAT,OPT4)
      INTEGER OPT4
C***  DETERMINES THE NUMBER OF A PARAMETERS FOR A GIVEN ITEM
      ADIM=1
      IF (OPT4.EQ.3) ADIM=NUMCAT+1
      RETURN
      END
      INTEGER FUNCTION BDIM (NUMCAT,OPT4)
      INTEGER OPT4
C***  DETERMINES THE NUMBER OF B PARAMETERS FOR A GIVEN ITEM
      BDIM=NUMCAT
      IF (OPT4.EQ.3) BDIM=NUMCAT+1
      RETURN
      END
      SUBROUTINE CHKINP (INUP,M,OPT4)
      INTEGER OPT4
C***  CHECKS FOR ERRORS IN THE INPUT DATA
C***  IF AN ERROR IS FOUND, A MESSAGE IS PRINTED AND THE PROGRAM
C***  HALTS
C
      IERR=0
      IF (INUP.LE.100) GO TO 1
      PRINT 4, INUP
      IERR=1
1     IF (M.LE.INUP) GO TO 2
      PRINT 5, M,INUP
      IERR=1
2     IF (1.LE.OPT4.AND.OPT4.LE.3) GO TO 3
      PRINT 6, OPT4
      IERR=1
3     IF (IERR.EQ.1) STOP
      RETURN
C
C
4     FORMAT (10X,*INPUT ERROR:  NO. OF ITEMS IN ITEM POOL =*,I5,/10X,*N
     1O. MUST BE .LE. 100*)
5     FORMAT (10X,*INPUT ERROR:  NO. ITEMS ADMINISTERED =*,I5,/10X,*NO.
     1MUST BE .LE. NO. OF ITEMS IN ITEM POOL =*,I5)
6     FORMAT (10X,*INPUT ERROR:  OPTION 4 =*,I3,* DOES NOT CORRES*,*POND
     1 TO ANY OF THE AVAILABLE RESPONSE MODELS*)
      END
      SUBROUTINE NOGRAD (IRESP,A,B,IITEMS,NCAT,INAD,EPS,MAXIT,SFORM,IFAI
     1L,THETA,NUMITS,TINFO,SE)
      EXTERNAL FDFVNO,SDRVNO
      DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100)
```

```
      CALL BISECT (FORVNO,IRESP,A,B,NITEMS,NCAT,INAD,5,GUESS)
      CALL NEWTRAP (FORVNO,SDRVNO,IRESP,A,B,NITEMS,NCAT,INAD,MAXIT,EPS,N
     1UMITS,GUESS,THETA,SDRV,IFAIL)
      SFORM=-SDRV
      IF (IFAIL.EQ.1) GO TO 1
      CALL NOINFO (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
      SE=1.0/SQRT(ABS(SDRV))
      RETURN
C
1     TINFO=-99.99
      SE=-99.99
      RETURN
      END
      FUNCTION IVALUE (IRESP,NCAT)
C***  CHECKS RESPONSE FOR SPECIAL CASES
C***  IVALUE RETURNS . . . 1  IF IRESP IS BEST RESPONSE
C***                       2  IF IRESP IS WORST RESPONSE
C***                       3  OTHERWISE
C
      IVALUE=3
      IF (IRESP.EQ.1) IVALUE=1
      IF (IRESP.EQ.(NCAT+1)) IVALUE=2
      RETURN
      END
      SUBROUTINE RCAT1 (A,B,THETA,TMINB0,TMINB1,P,ETOZ0,ETOZ1)
C***  COMPUTES VALUES NECESSARY FOR THE CALCULATION OF THE DERIV-
C***  ATIVES OF THE NORMAL OGIVE GRADED MODEL FOR THE SPECIAL CASE
C***  WHEN IRESP IS THE BEST RESPONSE
C
      TMINB0=THETA-B
      TMINB1=0.0
      Y=A*TMINB0
      P=CDFN(Y)
      ETOZ0=EXP(-Y*Y/2.0)
      ETOZ1=0.0
      RETURN
      END
      SUBROUTINE RCATN (A,B,THETA,TMINB0,TMINB1,P,ETOZ0,ETOZ1)
C***  COMPUTES VALUES NECESSARY FOR THE CALCULATION OF THE DER-
C***  IVATIVES OF THE NORMAL OGIVE GRADED MODEL FOR THE SPECIAL
C***  CASE WHEN IRESP IS THE WORST RESPONSE
C
      TMINB0=0.0
      TMINB1=THETA-B
      Y1=A*TMINB1
      P=1.0-CDFN(Y1)
      ETOZ0=0.0
      ETOZ1=EXP(-Y1*Y1/2.0)
      RETURN
      END
      SUBROUTINE RCATOT (A,B0,B1,THETA,TMINB0,TMINB1,P,ETOZ0,ETOZ1)
C***  COMPUTES VALUES NECESARY FOR THE CALCULATION OF DERIVATIVES OF
C***  THE NORMAL OGIVE GRADED MODEL FOR ALL OTHER CASES
C
      TMINB0=THETA-B0
      TMINB1=THETA-B1
      Y=A*TMINB0
      Y1=A*TMINB1
      P=CDFN(Y)-CDFN(Y1)
      ETOZ0=EXP(-Y*Y/2.0)
      ETOZ1=EXP(-Y1*Y1/2.0)
      RETURN
      END
      FUNCTION FORVNO (IRESP,INAD,NITEMS,NCAT,A,B,THETA)
      DIMENSION IRESP(100), INAD(100), NCAT(100), A(100,10), B(100,10)
C***  CALCULATES THE FIRST DERIVATIVE FOR THE NORMAL OGIVE GRADED MODEL
```

```
C
      SUM=0.0
      DO 5 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 5
      K=IRESP(I)
      J=IVALUE(K,NCAT(I))
      GO TO (1,2,3), J
C
C***  IRESP IS BEST RESPONSE
1     CALL FCAT1 (A(I,1),B(I,K),THETA,TMINB0,TMINB1,P,ETOZ0,ETOZ1)
      GO TO 4
C
C***  IRESP IS WORST RESPONSE
2     CALL FCATN (A(I,1),B(I,K-1),THETA,TMINB0,TMINB1,P,ETOZ0,ETOZ1)
      GO TO 4
C
C***  ALL OTHER RESPONSES
3     CALL FCATOT (A(I,1),B(I,K),B(I,K-1),THETA,TMINB0,TMINB1,P,ETOZ0,ET
     1OZ1)
4     CONTINUE
C
      IF (P.EQ.0.0) P=0.0001
      SUM=SUM+A(I,1)*(ETOZ0-ETOZ1)/P
5     CONTINUE
C
      FDRVNO=SUM/SQRT(2.0*3.142)
      RETURN
      END
      FUNCTION SDRVNO (IRESP,INAD,NITEMS,NCAT,A,B,THETA)
      DIMENSION IRESP(100), INAD(100), NCAT(100), A(100,10), B(100,10)
C***  CALCULATES SECOND DERIVATIVE FOR THE NORMAL OGIVE GRADED MODEL
C
      SUM=0.0
      ROOTPI=1.0/SQRT(2.0*3.142)
      DO 5 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 5
      K=IRESP(I)
      J=IVALUE(K,NCAT(I))
      GO TO (1,2,3), J
C
C***  IRESP IS BEST RESPONSE
1     CALL FCAT1 (A(I,1),B(I,K),THETA,TMINB0,TMINB1,P,ETOZ0,ETOZ1)
      GO TO 4
C
C***  IRESP IS WORST RESPONSE
2     CALL FCATN (A(I,1),B(I,K-1),THETA,TMINB0,TMINB1,P,ETOZ0,ETOZ1)
      GO TO 4
C
C***  ALL OTHER RESPONSES
3     CALL FCATOT (A(I,1),B(I,K),B(I,K-1),THETA,TMINB0,TMINB1,P,ETOZ0,ET
     1OZ1)
4     CONTINUE
C
      IF (P.EQ.0.0) P=0.0001
      SUM1=A(I,1)*ROOTPI*(ETOZ0-ETOZ1)/P
      SUM1=-SUM1*SUM1
      SUM2=-(A(I,1)**3)*ROOTPI*((TMINB0*ETOZ0)-(TMINB1*ETOZ1))/P
      SUM=SUM+SUM1+SUM2
5     CONTINUE
C
      SDRVNO=SUM
      RETURN
      END
      SUBROUTINE NCINFO (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
      DIMENSION A(100,10), B(100,10), NCAT(100), INAD(100)
C***  COMPUTES INFORMATION FOR GRADED NORMAL OGIVE MODEL AT GIVEN
```

```
C***  VALUE OF THETA
C
      TINFO=0.0
      ROOTPI=1.0/SQRT(2.0*3.142)
C***  LOOP OVER ITEMS
      DO 5 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 5
C
C***  INITIALIZATION--VALUES CALCULATED FOR FIRST CATEGORY OF ITEM I
      Y=A(I,1)*(THETA-B(I,1))
      P0=CDFN(Y)
      P1=0.0
      ETOZ0=EXP(-Y*Y/2.0)
      ETOZ1=0.0
      KATGRY=0
C
C***  LOOP OVER ALL THE CATEGORIES OF ITEM I
1     KATGRY=KATGRY+1
      P=P0-P1
      IF (P.EQ.0.0) P=0.0001
      FDRVP=A(I,1)*ROOTPI*(ETOZ0-ETOZ1)
      TINFO=TINFO+(FDRVP*FDRVP)/P
C
      ETOZ1=ETOZ0
      P1=P0
C
      IF (KATGRY-(NCAT(I)+1)) 2,3,4
C***  CURRENT CATEGORY UNDER CONSIDERATION IS NOT ONE OF THE EXTREMES
2     Y=A(I,1)*(THETA-B(I,KATGRY))
      P0=CDFN(Y)
      ETOZ0=EXP(-Y*Y/2.0)
      GO TO 1
C***  LAST CATEGORY OF AN ITEM IS BEING CONSIDERED
3     P0=1.0
      ETOZ0=0.0
      GO TO 1
C***  ALL CATEGORIES FOR ITEM I HAVE BEEN EXAMINED
4     CONTINUE
C
5     CONTINUE
      RETURN
      END
      SUBROUTINE LOGRAD (IRESP,A,B,NITEMS,NCAT,INAD,EPS,NITER,SFORM,IFAI
     1L,THETA,NUMITS,TINFO,SE)
      EXTERNAL FDRVLL,SDRVLL
      DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100)
      CALL BISECT (FDRVLL,IRESP,A,B,NITEMS,NCAT,INAD,5,GUESS)
      CALL NEWTRAP (FDRVLL,SDRVLL,IRESP,A,B,NITEMS,NCAT,INAD,NITER,EPS,N
     1UMITS,GUESS,THETA,SDRV,IFAIL)
      SFORM=-SDRV
      IF (IFAIL.EQ.1) GO TO 1
      CALL LLINFO (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
      SE=1.0/SQRT(ABS(SDRV))
      RETURN
C
1     TINFO=-99.99
      SE=-99.99
      RETURN
      END
      SUBROUTINE CALCP (IRESP,INAD,NCAT,A,B,NITEMS,THETA,P)
      COMMON D
      DIMENSION IRESP(100), INAD(100), NCAT(100), B(100,10), P(100,2), A
     1(100,10)
C**** CALCULATES UPPER AND LOWER P FOR EACH ITEM WITH GIVEN ANSWER VECT
      DO 4 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 4
```

```
      J=IRESP(I)
      IF (J.EQ.1) GO TO 1
      P(I,1)=1.0/(1.0+EXP(-D*A(I,1)*(THETA-B(I,J-1))))
      GO TO 2
1     P(I,1)=0.0
2     IF (J.EQ.(NCAT(I)+1)) GO TO 3
      P(I,2)=1.0/(1.0+EXP(-D*A(I,1)*(THETA-B(I,J))))
      GO TO 4
3     P(I,2)=1.0
4     CONTINUE
      RETURN
      END
      FUNCTION FORVLL (IRESP,INAD,NITEMS,NCAT,A,B,THETA)
      COMMON D
      DIMENSION P(100,2), A(100,10), B(100,10), INAD(100), IRESP(100), N
     1CAT(100)
C***  CALCULATES FIRST DERIVATIVE OF LOG-LIKE FUNCTION
      SUM=0.0
      CALL CALCP (IRESP,INAD,NCAT,A,B,NITEMS,THETA,P)
      DO 1 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 1
      SUM=SUM+A(I,1)*(1.0-P(I,1)-P(I,2))
1     CONTINUE
      FORVLL=SUM*D
      RETURN
      END
      FUNCTION SORVLL (IRESP,INAD,NITEMS,NCAT,A,B,THETA)
      COMMON D
      DIMENSION P(100,2), A(100,10), B(100,10), INAD(100), IRESP(100), N
     1CAT(100)
C***  CALCULATES SECOND DERIVATIVE OF LOGLIKE FUNCTION
      SUM=0.0
      CALL CALCP (IRESP,INAD,NCAT,A,B,NITEMS,THETA,P)
      DO 1 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 1
      Q1=1.0-P(I,1)
      Q2=1.0-P(I,2)
      P1=P(I,2)-P(I,1)
      DIFF1=2.0*Q1-1.0
      DIFF2=2.0*Q2-1.0
      R1=P(I,1)*Q1
      R2=P(I,2)*Q2
      SUM=SUM+(A(I,1)**2/P1)*(-DIFF1*R1+DIFF2*R2-((R1-R2)**2)/P1)
1     CONTINUE
      SORVLL=D*D*SUM
      RETURN
      END
      SUBROUTINE PCAT (A,B,THETA,ITEM,NUMCAT,PLOWER,PUPPER)
      COMMON D
      DIMENSION B(100,10), PLOWER(10), PUPPER(10)
C***  CALCULATES P"S FOR ALL RESPONSE CATEGORIES OF A GIVEN ITEM
C
      PLOWER(1)=0.0
      DO 1 I=1,NUMCAT
      PUPPER(I)=1.0/(1.0+EXP(-D*A*(THETA-B(ITEM,I))))
      PLOWER(I+1)=PUPPER(I)
1     CONTINUE
      PUPPER(NUMCAT+1)=1.0
      RETURN
      END
      SUBROUTINE LLINFO (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
      COMMON D
      DIMENSION A(100,10), B(100,10), NCAT(100), INAD(100)
      DIMENSION PUPPER(10), PLOWER(10)
C***  COMPUTES INFORMATION FOR THE GRADED LOGISTIC MODEL AT A GIVEN
C***  VALUE OF THETA
```

```
C
      TINFO=0.0
      DO 2 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 2
      CALL PCAT (A(I,1),B,THETA,I,NCAT(I),PLOWER,PUPPER)
C
C***  LOOP OVER ALL THE RESPONSE CATEGORIES OF ITEM I
      NCATEG=NCAT(I)+1
      DO 1 J=1,NCATEG
      QUPPER=1-PUPPER(J)
      QLOWER=1-PLOWER(J)
      P=PUPPER(J)-PLOWER(J)
      IF (P.EQ.0.0) P=0.0001
      FDRVP=D*A(I,1)*(PUPPER(J)*QUPPER-PLOWER(J)*QLOWER)
      TINFO=TINFO+(FDRVP*FDRVP)/P
1     CONTINUE
2     CONTINUE
      RETURN
      END
      SUBROUTINE NOMLOG (IRESP,A,B,NITEMS,NCAT,INAD,EPS,MAXIT,SFORM,IFAI
     1L,THETA,NUMITS,TINFO,SE)
      EXTERNAL FDRVNL
      DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100)
      CALL BISECT (FDRVNL,IRESP,A,B,NITEMS,NCAT,INAD,5,GUESHI,GUESLO)
      CALL SECANT (FDRVNL,IRESP,A,B,NITEMS,NCAT,INAD,MAXIT,EPS,GUESHI,GU
     1ESLO,NUMITS,THETA,SDRV,IFAIL)
      SFORM=-SDRV
      IF (IFAIL.EQ.1) GO TO 1
      CALL NLINFO (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
      SE=1.0/SQRT(ABS(SDRV))
      RETURN
C
1     TINFO=-99.99
      SE=-99.99
      RETURN
      END
      FUNCTION FDRVNL (IRESP,INAD,NITEMS,NCAT,A,B,THETA)
      DIMENSION IRESP(100), INAD(100), NCAT(100), A(100,10), B(100,10)
C***  CALCULATES FIRST DERIVATIVE OF NOMINAL LOGISTIC FUNCTION
C***  NOTE:  FOR THIS MODEL, THE A"S ARE THE SLOPE PARAMETERS
C***         AND THE B"S ARE THE INTERCEPT PARAMETERS
C
      SUM=0.0
      DO 2 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 2
      XNUM=0.0
      DENOM=0.0
      NUMCAT=NCAT(I)+1
      DO 1 J=1,NUMCAT
      CONST=A(I,IRESP(I))-A(I,J)
      ARG=A(I,J)*THETA+B(I,J)
      EZ=EXP(ARG)
      XNUM=XNUM+CONST*EZ
      DENOM=DENOM+EZ
1     CONTINUE
      SUM=SUM+XNUM/DENOM
2     CONTINUE
      FDRVNL=SUM
      RETURN
      END
      SUBROUTINE NLINFO (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
      DIMENSION A(100,10), B(100,10), NCAT(100), INAD(100)
      DIMENSION E(10)
C***  COMPUTES INFORMATION FOR THE NOMINAL LOGISTIC FUNCTION AT A
C***  GIVEN VALUE OF THETA
C
```

```
      TINFO=0.0
C***  LOOP OVER THE ITEMS
      DO 4 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 4
      NCATEG=NCAT(I)+1
C
C***  COMPUTE THE DENOMINATOR USED TO CALCULATE P AND THE FIRST
C***  DERIVATIVE OF P--IT IS THE SAME VALUE FOR ALL POSSIBLE RE-
C***  SPONSES TO ITEM I
      DENOM=0.0
      DO 1 K=1,NCATEG
      E(K)=EXP(A(I,K)*THETA+B(I,K))
      DENOM=DENOM+E(K)
1     CONTINUE
C
C***  SUM OVER ALL POSSIBLE RESPONSES
      DO 3 J=1,NCATEG
      P=E(J)/DENOM
C
C***  CALCULATE THE FIRST DERIVATIVE OF P
      DRVNUM=0.0
      DO 2 K=1,NCATEG
      DRVNUM=DRVNUM+E(K)*(A(I,J)-A(I,K))
2     CONTINUE
      FDRVP=(E(J)*DRVNUM)/(DENOM*DENOM)
C
      TINFO=TINFO+(FDRVP*FDRVP)/P
3     CONTINUE
4     CONTINUE
      RETURN
      END
      SUBROUTINE CHKRSP (IRESP,IOMIT,INAD,NCAT,NITEMS,NAME,ID,INADS)
      DIMENSION IRESP(100), INAD(100), NCAT(100), NAME(2), INADS(100)
C***  DELETES OMITTED ITEMS FOR A SUBJECT FROM LIST OF ITEMS ____
C***  ADMINISTERED (RESULTS RETURNED IN INADS)  AND CHECKS TO SEE
C***  IF ALL RESPONSES ARE VALID, IF NOT AN ERROR MESSAGE IS WRITTEN
C***  AND THE PROGRAM HALTS
C
      DO 2 I=1,NITEMS
      NUMCAT=NCAT(I)+1
      INADS(I)=INAD(I)
      IF (IRESP(I).NE.IOMIT) GO TO 1
      INADS(I)=0
      GO TO 2
C
C***  CHECK FOR INVALID RESPONSE
1     IF ((1.LE.IRESP(I)).AND.(IRESP(I).LE.NUMCAT)) GO TO 2
      PRINT 3, NAME,ID,IRESP(I),NUMCAT
      STOP
C
2     CONTINUE
      RETURN
C
C
3     FORMAT (10X,*ERROR IN DATA:  SUBJECT = *,2A10,* ID = *,A9,* HAS IL
     1LEGAL RESPONSE =*,I3,/10X,*RESPONSES MUST BE*,* BETWEEN 1 AND NUMB
     2ER OF CATEGORIES =*,I3,* INCLUSIVE*)
      END
      SUBROUTINE CHKVEC (IRESP,INAD,NCAT,NITEMS,ICHK,NBEST,NANS)
      DIMENSION IRESP(100), INAD(100), NCAT(100)
C     CHKVEC TESTS THE RAW RESPONSE VECTOR TO DETERMINE IF
C     IF IT IS ONE OF THE FOLLOWING THREE CASES:
C***     ALL BEST RESPONSES...ICHK SET TO 3
C***     ALL WORST RESPONSES...ICHK SET TO 2
C***     NO RESPONSES.....ICHK SET TO 1
C***     OTHERWISE.....ICHK SET TO 4
```

```
      NANS=0
      NWORST=0
      NBEST=0
      DO 1 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 1
      NANS=NANS+1
      IF (IRESP(I).EQ.1) NBEST=NBEST+1
      IF (IRESP(I).EQ.NCAT(I)+1) NWORST=NWORST+1
1     CONTINUE
C
      ICHK=4
      IF (NANS.EQ.0) ICHK=1
      IF (NWORST.EQ.NANS) ICHK=2
      IF (NBEST.EQ.NANS) ICHK=3
      RETURN
      END
      SUBROUTINE BISECT (F1,IRESP,A,B,NITEMS,NCAT,INAD,NIT,BMID,BLAST)
      DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100),
     1P(100,2)
C***  CALCULATES APPROXIMATE ROOT OF F1 BY BISECTION,BISECTING THE INTER
C***  NIT( NUMBER OF ITERATIONS) TIMES.  BMID IS BEST CURRENT GUESS AT T
C***  BLAST IS THE PREVIOUS VALUE OF BMID. IT IS USED AS THE SECOND
C***  INITIAL GUESS FOR THE SECANT METHOD.
C
C     INITIALIZE LEFT BOUND AND F1(BOUND), AND RIGHT BOUND,F1(BOUND)
      BL=-5.0
      BR=5.0
      BMID=0.0
      TL=F1(IRESP,INAD,NITEMS,NCAT,A,B,BL)
      TR=F1(IRESP,INAD,NITEMS,NCAT,A,B,BR)
C     TEST FOR NO ROOT IN INTERVAL,AND RETURN IF NOT POSSIBLE
      IF ((TL*TR).GT.0.0) RETURN
C     NOW CALCULATE BISECTIONS NIT TIMES
      DO 3 I=1,NIT
      TMID=F1(IRESP,INAD,NITEMS,NCAT,A,B,BMID)
      IF ((TMID*TL).GT.0.0) GO TO 1
      BR=BMID
      GO TO 2
1     TL=TMID
      BL=BMID
2     BMID=(BL+BR)/2.0
3     CONTINUE
      BLAST=BR
      IF (TL.EQ.TMID) BLAST=BL
      RETURN
      END
      SUBROUTINE NEWTRAP (F1,F2,IRESP,A,B,NITEMS,NCAT,INAD,NITER,EPS,NUM
     1ITS,GUESS,THETA,SDRV,IFAIL)
      DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100)
C     CALCULATES ROOT OF F1 GIVEN ITS FIRST DERIVATIVE F2 AND AN INITIAL
C***   GUESS.  UTILIZES NEWTON-RAPHSONS METHOD
C
C     INITIALIZE
      NUMITS=0
      THETA=GUESS
C***  LOOP UNTIL ERR IS LESS THAN EPS OR NUMBER OF ITERATIONS BECOMES TO
1     SDRV=F2(IRESP,INAD,NITEMS,NCAT,A,B,THETA)
      FDRV=F1(IRESP,INAD,NITEMS,NCAT,A,B,THETA)
      ERR=FDRV/SDRV
      THETA=THETA-ERR
      NUMITS=NUMITS+1
C     EXIT LOOP CRITERION
      IF ((NUMITS.LT.NITER).AND.(ABS(ERR).GT.EPS)) GO TO 1
C***  END LOOP,  TEST FOR FAILURE AND SET IFAIL
      IFAIL=0
      IF (ABS(ERR).LT.EPS) RETURN
```

```
      IFAIL=1
      THETA=-99.99
      SDRV=99.99
      RETURN
      END
      SUBROUTINE SECANT (F1,IRESP,A,B,NITEMS,NCAT,INAD,MAXIT,EPS,GUESHI,
     1GUESLO,NUMITS,THETA,SLOPE,IFAIL)
      DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100)
C***  USES THE SECANT METHOD TO CALCULATE THE ROOT, THETA, OF THE
C***  FUNCTION F1
C***  GUESHI AND GUESLO ARE THE TWO INITIAL GUESSES AT THE ROOT
C***  REQUIRED BY THE SECANT METHOD
C
      NUMITS=0
      THETA=GUESHI
      TLAST=GUESLO
      FLAST=F1(IRESP,INAD,NITEMS,NCAT,A,B,TLAST)
C
C***  LOOP UNTIL CONVERGENCE OR NONCONVERGENCE IS ESTABLISHED
1     FCUR=F1(IRESP,INAD,NITEMS,NCAT,A,B,THETA)
      IF (FCUR.EQ.FLAST) GO TO 2
      SLOPE=(THETA-TLAST)/(FCUR-FLAST)
      CHANGE=FCUR*SLOPE
      TLAST=THETA
      FLAST=FCUR
      THETA=THETA-CHANGE
      NUMITS=NUMITS+1
      IF (ABS(CHANGE).GT.EPS.AND.NUMITS.LT.MAXIT) GO TO 1
C
      IFAIL=0
      SLOPE=1.0/SLOPE
      IF (ABS(CHANGE).LE.EPS) RETURN
C***  SECANT METHOD DOES NOT CONVERGE IN MAXIT ITERATIONS
      IFAIL=1
      THETA=-99.99
      SLOPE=-99.99
      RETURN
C
C***  ERROR:  SECANT METHOD CANNOT BE USED ON F1
2     PRINT 3
      IFAIL=1
      THETA=-88.88
      SLOPE=-88.88
      RETURN
C
3     FORMAT (10X,*HORIZONTAL SLOPE FOUND IN FIRST DERIVATIVE FOR *,*CUR
     1RENT SUBJECT.*,/10X,*SECANT METHOD CANNOT BE USED.*)
      END
```

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